CHARACTERIZATION OF VARIOUS POWER QUALITY DISTURBANCES BASED ON SIGNAL PROCESSING AND ARTIFICIAL INTELLIGENCE SCHEME

SATYAJIT BEHERA (111EE0198)

SUDHANSHU SEKHAR SEND (111EE0232)

DEPARTMENT OF ELECTRICAL ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA

CHARACTERIZATION OF
VARIOUS POWER QUALITY DISTURBANCES
BASED ON
SIGNAL PROCESSING
AND
ARTIFICIAL INTELLIGENCE SCHEME

A dissertation submitted in fractional satisfaction the necessities

for award of the degree of

Bachelor of Technology in "Electrical Engineering"

By

SATYAJIT BEHERA (111EE0198)

SUDHANSHU SEKHAR SEND (111EE0232)

Under the surveillance of

PROF. SANJEEB MOHANTY

Department of Electrical Engineering

National Institute of Technology

Rourkela-769008 (ODISHA)

AUTHENTICATION

This is for the certification that the thesis titled "**Classification of Various Power Quality Disturbances Based on Signal Processing and Artificial Intelligence Scheme**", presented by **Satyajit Behera (111EE0198) and Sudhanshu Sekhar Send (111EE0232)** in fractional satisfaction of the requirements for the award of Batchelor of Technology in Electrical Engineering during 2014-2015 at the National Institute of Technology, Rourkela is a bona fide work carried out by them under my oversight.

The thesis is purely based upon their own work and is not submitted elsewhere for any degree or diploma.

Date

Prof. Sanjeeb Mohanty

Supervisor

Dept. of Electrical Engineering

N I T ROURKELA

ACKNOWLEDGEMENTS

We are truly indebted and wish to express our gratitude towards our guide Prof. Sanjeeb Mohanty for his continuous assistance, inspiration, motivation and encouragement in every stage of the research work. His keenness for guidance and his advices were invaluable.

We are also thankful to Head of Electrical Engineering, NIT Rourkela and to all the staffs of the Department for their constructive suggestions and assistance.

We are grateful to all our friends who have contributed their precious time and effort to help us.

Finally, we are always indebted to our family for their continuous support and motivation.

SATYAJIT BEHERA (111EE0198)
SUDHANSHU SEKHAR SEND (111EE0232)

Abstract

These days the electrical power quality has become a vital issue for the utilities and the consumers. Use of non-linear and sensitive loads add gradual deterioration of power quality. To improve power quality, automatic classification of power quality disturbances(PQDs) is much essential, which are also important for protection of transmission system network. Disturbances are mostly transient and temporary, thereby necessitate suitable method to analyze PQDs. In this paper a combined technique in the form of wavelet transform(WT) in association with fuzzy expert system is used for characterizing PQ disturbances. A no of PQ signals are developed and decomposed using WT method for nearly exact detection of disturbances. Energy and Total Harmonic Distortion (THD) of all PQ disturbances are extracted through discrete wavelet transform (DWT) and are used in the fuzzy expert system to detect and classify different disturbances accurately. The fuzzy system used classifies the disturbances and confirms the presence of harmonics.

INDEX

CHAPTER 4 IMPLEMENTATION OF FUZZY EXPERT SYSTEM TO CHARACTERIZE PQ

CHAPTER 5 CONCLUSION & FUTURE SCOPE OF WORK

REFERENCE

Figures

Tables

CHAPTER 1

INTRODUCTION

1.1 Preface

Electrical energy systems, voltages and especially currents are now less sinusoidal and periodical and even steady state behaviour may be absolutely lost owing to the use of non-linear loads and power electronic based systems and inverters used in renewable energy sourced generating systems are the sources of disturbances, which worsen the waveform shape of the power system [2]. The equipment used with electrical utility are very sensitive to power quality (PQ) variation. The Poor PQ may cause drastic problems for the equipment like reduced efficiency, shorter lifespan and malfunctioning. Research work has found that poor PQ are due to various power line disturbances. Hence removal of PQ disturbances has become a major concern to enhance the quality and hence the detection of disturbance type happening in power system so as to detect disturbance sources and mitigation can be executed. Disturbances are transient and require suitable methods for characterization of PQ disturbances. Fourier transform is not a proper tool for analysis of PQ disturbances as it provides spectral information of the signal only and no time localization data that is essential for finding start and end time and disturbance interval[1]. The Short Time Fourier Transform (STFT) is another tool suited for stationary signals [2-4]. However STFT does not recognize the non-stationary signal dynamics owing to the limited fixed window width [2]. The Discrete Wavelet Transform (DWT) is preferred as it results in a better time-frequency resolution [5].

1.2 Literature Analysis

Various research works in the area of application of digital signal processing techniques to power quality analysis has been conducted. Santoso et al.[6] used the Wavelet Transform (WT) along with Fourier Transform (FT) to detect unique features in voltage and current waveforms for characterizing power quality events. The WT is applied to transient phenomena whereas FT characterizes steady state phenomena.

Wright et al. [2] used STFT for PQ analysis. WT is an excellent tool for non stationary signals and is superior to STFT. It analyzes the signal in time scale representation. The DWT is used to look at the signal at different scales or resolution [7-9].

Abdelazeem et al [7] used a hybrid technique to detect and characterize PQ disturbances using WT,. L.C Saikia et al [8] have proposed a technique basing on the WT and the artificial neural network tor characterize PQDs.

In the recent past WT in association with artificial intelligence scheme is used extensively for characterizing power quality.

1.3 Purpose of the Work

Literature survey reveals that the discrete wavelet transformation (DWT) is a powerful computing and mathematical tool that is used independently for power quality analysis. The main reason for power quality disturbance are the power line disturbances and to mitigate the above problem we need to detect and classify the PQ disturbances for further processing. The main idea is to study the signal at various resolution. Here the developed signals are decayed through WT and smoothness is observed. This shows that each disturbance has unique deflection from the pure sinusoidal form and this provides a reliable method. The objective of this work is

- To generate various PQ events
- To detect the disturbances using WT
- To extract features from the decomposed signals
- Classification of PQ disturbances using fuzzy expert system

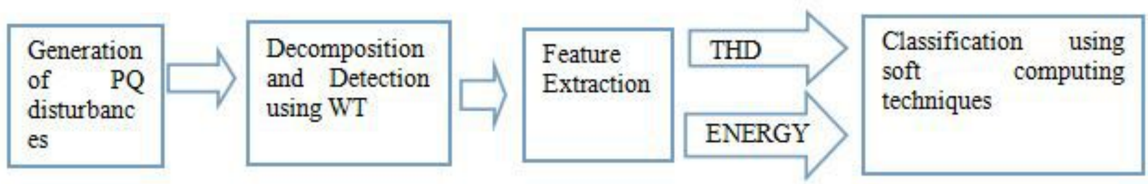

Figure 1.1 Basic block diagram of the method adopted

Figure 1.1 shows the method used in this work. In the first stage the different PQ disturbances are developed followed by decomposing through WT and the disturbance instants and the disturbance type are detected. Then the features like energy and total harmonic distortion (THD) are obtained from the decomposed signal. In the final stage these features are used for characterization of various PQ disturbances using fuzzy expert system.

1.4 Thesis Layout

Chapter 1 analyzes the literature on various power quality issues and classification of PQ disturbances using wavelet transform in conjunction with the artificial intelligence scheme. The objective and a brief description of the work is presented.

Chapter 2 discusses the wavelet transform mechanism and decomposition algorithm and then various PQ disturbances are simulated and decayed using WT. Choice of mother wavelet and selection of maximum decomposition levels are mentioned.

Chapter 3 extracts THD and Energy from various PQ disturbances which is used as input to the fuzzy expert system.

Chapter 4 designs a fuzzy expert system for characterizing various PQ disturbances and classification accuracy of each PQ disturbance was calculated.

Chapter 5 summarizes the results and future scope of work is discussed in brief.

CHAPTER 2

DECOMPOSITION

USING

WAVELET TRANSFORM

2.1. Preface

In present days wavelet transform (WT) is emerged as a useful technique in detection of PQ disturbances. The basis function used in WT is wavelet function that scales itself as per base frequency. The method gives accurate results as the basis function used here is a wavelet whereas FT and STFT uses an exponential function as basis function. WT decomposes the signal into various levels of frequency and presents as wavelet coefficients. Based upon the signal types, for continuous time signal continuous wavelet transform (CWT) and for discrete time signal discrete wavelet transform (DWT) are used. As power signals used in the work are of discrete nature, thereby decomposition through DWT is adopted. Various PQ disturbances are developed through MATLAB programme and decayed using decomposition algorithm and disturbance is spotted and its type is identified.

2.2 Discrete Wavelet Transform (DWT)

DWT is consist of two stages. The first stage determines wavelet coefficients that represent the signal *X(n)* in wavelet domain. The second stage involves calculation of both approximated and detailed version of original signal, these wavelet coefficients are termed cA1(n) and cD1(n).

$$cA_1(n) = \sum_k S(n).h_d(-k+2n) \qquad \text{............... (2.1)}$$

$$cD_1(n) = \sum_k S(n).g_d(-k+2n) \qquad \text{............... (2.2)}$$

Similarly subsequent level decomposition are obtained. The above algorithm is depicted in Figure 2.1. The signal *X(n)* is fed to a band pass filter, a combination of a set of low pass and high pass filter, followed by sub-sampling of two in each stage as per Nyquist's rule to avoid data redundancy issue. Once the wavelet coefficients are found the DWT is obtained by reconstructing the corresponding wavelet coefficients at various levels. The reverse process of Wavelet decomposition is the reconstruction algorithm, shown in Figure 2.2 . The WT of *X(t)* is stated as

$$WTx(a,b) = \int_{-\infty}^{\infty} X(t)\psi_{a,b}^{*}dt \qquad \text{..............(2.3)}$$

$$where \;\; \psi_{a,b}(t) = \psi((t-b)/a)/\sqrt{a} \qquad \text{............. (2.4)}$$

is a translated version of the mother wavelet Ψ(t). Here 1/√a is a value used for normalization of *Ψa,b(t)* to have spectrum power same as mother wavelet, parameter *a* is frequency domain property and *b* is time domain property of Ψ(t). DWT introduces digital filter property whose anatomy is depicted in Figure 2.1. The low pass filter of the band pass filter estimates X(t) and high pass filter gives the loss of details in approximation. The details are high frequency low scale component and the approximations are low frequency high scale component.

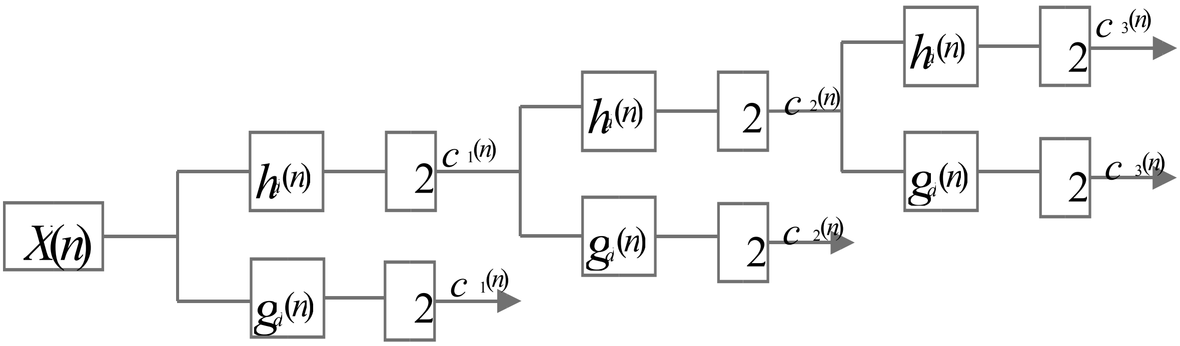

Figure 2.1 Decomposition algorithm

Where hd[n] = Impulse response of LP filter

gd[n] = Impulse response of HP filter

X(n) = Discretized original signal

cA1(n) =Approximate coefficient of level 1 decomposition/output of first LPF

cA2 (n) =Approximate coefficient of level 2 decomposition/output of 2nd LPF

cA3 (n) =Approximate coefficient of level 3 decomposition/output of 3rd LPF

cD1(n) = Detail coefficient of level 1 decomposition/output of first HPF

cD2(n) = Detail coefficient of level 2 decomposition/output of 2nd HPF

cD3(n) = Detail coefficient of level 3 decomposition/output of 3rd HPF

Level 1 decomposition : X(n) =cA1(n) +cD1(n)

Level 2 decomposition : X(n) =cA2(n) +cD2(n) +cD1(n)

Level 3 decomposition : X(n) =cA3(n) +cD3(n) +cD2(n) + cD1(n)

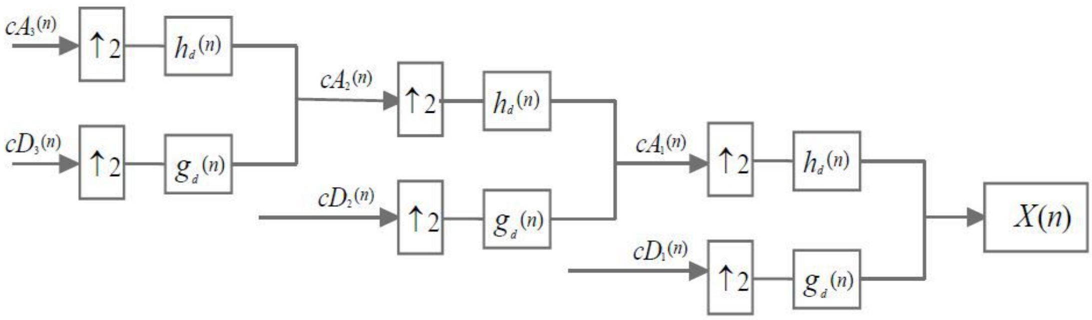

Figure 2.2 Reconstruction algorithm

2.2.1 Choice of Mother Wavelet

A vital issue in PQ disturbances decomposition is the selection of mother wavelet as it facilitates exact identification of disturbances. The test signal is multiplied with it to acquire the scaled and translated version of the signal while decomposing into various levels. Haar, Symlet, Daubechies, Morlet etc are various mother wavelets available. Literature study reveals that Daubechies wavelet gives the desired result for PQ analysis.. Out of various Daubechies wavelet like Db2, Db3, Db4, Db5 Db6, Db7 Db8, and Db10etc, Db4 and Db6 gives good result in the fast transient case owing to compactness of these wavelets and in slow transient case Db8 and Db10 gives better result.

2.2.2 Selection of maximum decomposition level

Maximum decomposition level of a signal in DWT, is obtained by

$$J_{max} = fix\ (log_2\ n) \qquad \text{..............} \ (2.5)$$

where n depicts length of signal and *fix* rounds the value in the bracket to nearest integer. Practically maximum decomposition level is selected according to the convenience and requirement.

2.3 PQ disturbances generation

Various PQ events are generated with unity magnitude using MATLAB.

2.3.1 Signal specification

Time period, T_s =0.5 sec, sampling frequency, f_s =6.4 Kilo Hz, f=50 Hz, Number of cycles=25, Number of samples/cycle=128, Net Sampling points=3200.

2.3.2 Parametric model of PQ disturbances

Table 2.1 Equations for PQ signals

PQ disturbance	Model	Parameter variations
Sinusoidal Voltage	$X(t)=\sin(wt)$	$W=2\pi*50\ rad/s$
Voltage Sag	$X(t)=[1-\alpha(u(t-t_1)-u(t-t_2))]\sin(wt)$	$0.1 \le \alpha \le 0.9$ $T \le t_2\text{-}t_1 \le 9T$
Voltage Swell	$X(t)=[1+\alpha(u(t-t_1)-u(t-t_2))]\sin(wt)$	$0.1 \le \alpha \le 0.8$ $T \le t_2\text{-}t_1 \le 9T$
Interruption	$X(t)=[1-\alpha(u(t-t_1)-u(t-t_2))]\sin(wt)$	$0.9 \le \alpha \le 1$ $T \le t_2\text{-}t_1 \le 9T$
Flicker	$X(t)=[1+\alpha\sin(2\pi\beta t)]\sin(wt)$	$0.1 \le \alpha \le 0.2;\ 5 \le \beta \le 20$
Harmonics	$X(t)=\alpha_1\sin(wt)+\alpha_3\sin(3wt)+$ $\alpha_5\sin(5wt)+\alpha_7\sin(7wt)$	$0.05 \le \alpha_3, \alpha_5, \alpha_7 \le 0.15$ $\Sigma(\alpha_i)^2=1$
Voltage sag with harmonics	$X(t)=[1-\alpha(u(t-t_1)-u(t-t_2))]*$ $[\alpha_1\sin(wt)+\alpha_3\sin(3wt)+\alpha_5\sin(5wt)]$	$0.05 \le \alpha_3,\ \alpha_5 \le 0.15$ $\Sigma(\alpha_i)^2=1$ $0.1 \le \alpha \le 0.9$ $T \le t_2\text{-}t_1 \le 9T$
Voltage swell with harmonics	$X(t)=[1+\alpha(u(t-t_1)-u(t-t_2))]*$ $[\alpha_1\sin(wt)+\alpha_3\sin(3wt)+\alpha_5\sin(5wt)]$	$0.05 \le \alpha_3,\ \alpha_5 \le 0.15$ $\Sigma(\alpha_i)^2=1$ $0.1 \le \alpha \le 0.8$ $T \le t_2\text{-}t_1 \le 9T$
Oscillatory Transient	$x(t)=\sin(wt)+\alpha\exp(-(t-t1)\tau)*$ $(u(t-t1)-u(t-t2)*\sin(2\pi f_n t)$	$0.1 \le \alpha \le 0.8$ $0.5T \le t_2\text{-}t_1 \le 3T$ $300 \le f_n \le 900$ $8 \le \tau \le 40$

where α depicts level of swell or sag. The unit step function *u(t)* gives interval of disturbances present in pure sine wave. By varying α position of *u(t)* is varied suitably and a large number of signals are obtained . The point on the wave *is* instant on the sinusoid when a disturbance starts and is monitored by the position of unit step function *u(t).* The momentary interruption with α is taken for varying the amplitude during interruption. Using the above parametric model hundred no of PQ events in each class of the disturbance are generated.

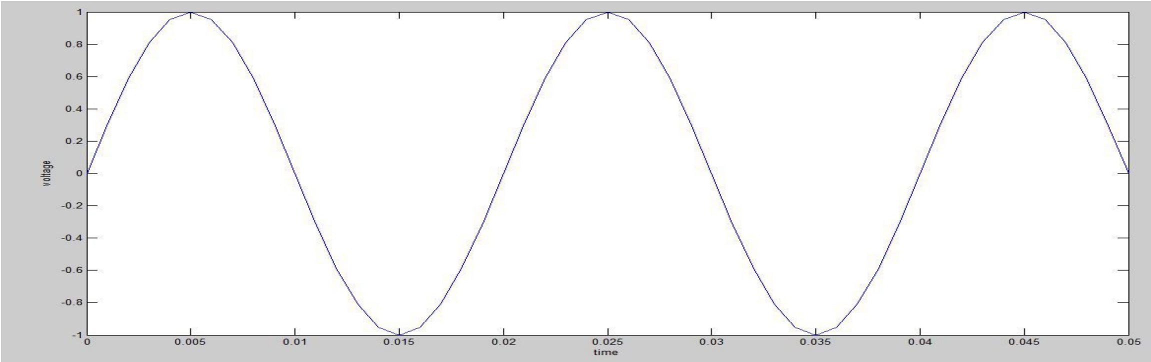

Figure 2.3 : Sinusoidal Voltage

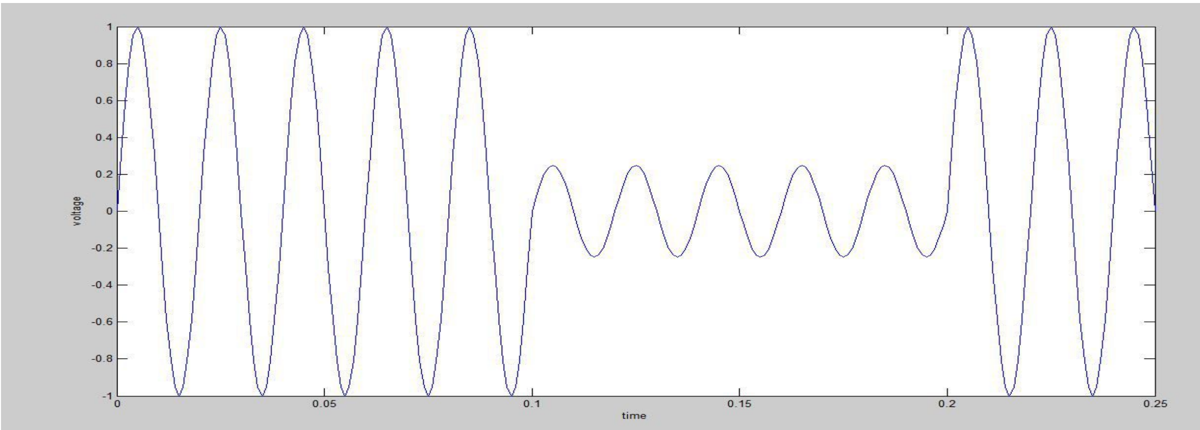

Figure 2.4 : Voltage sag

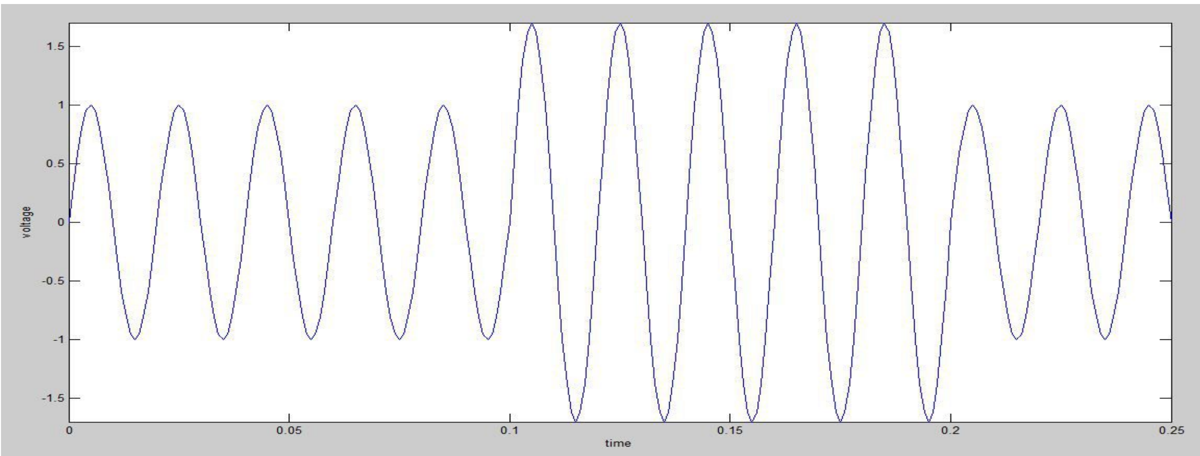

Figure 2.5 : Voltage swell

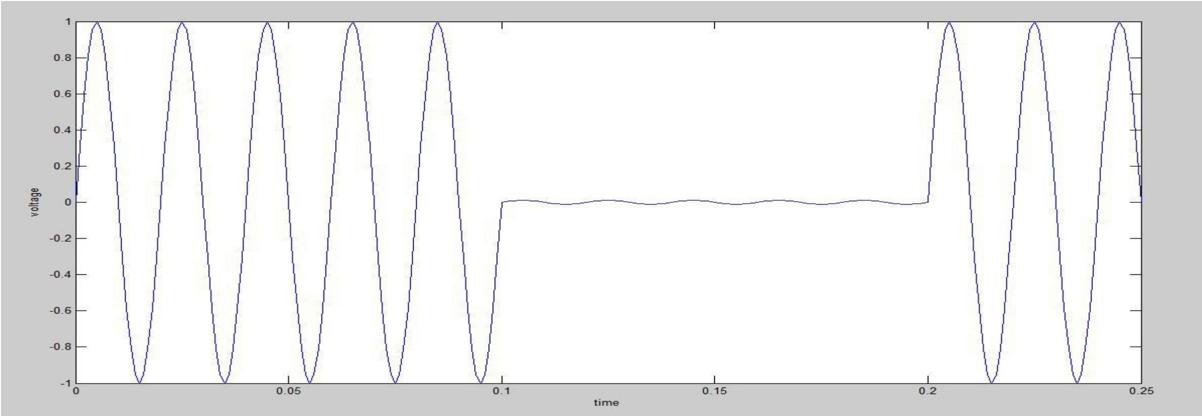

Figure 2.6: Voltage interruption

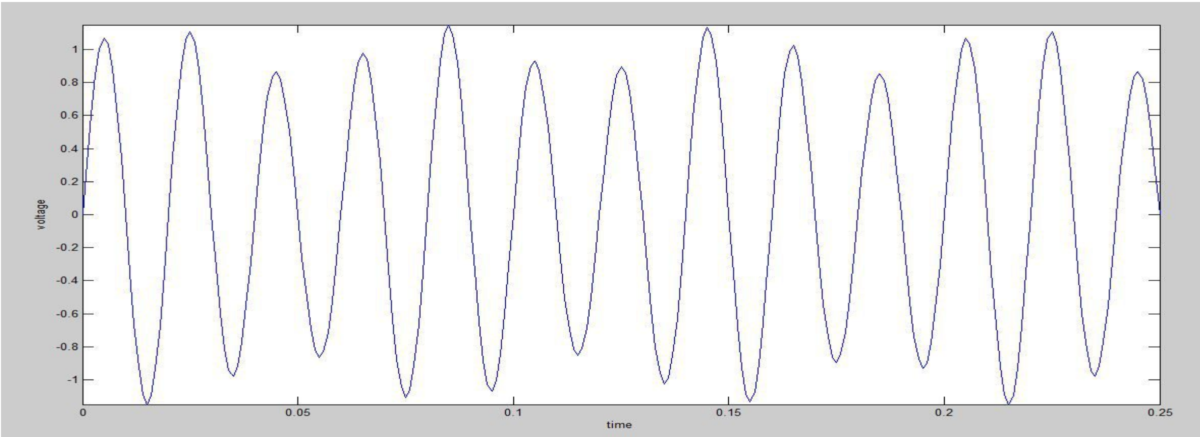

Figure 2.7 : Voltage flicker

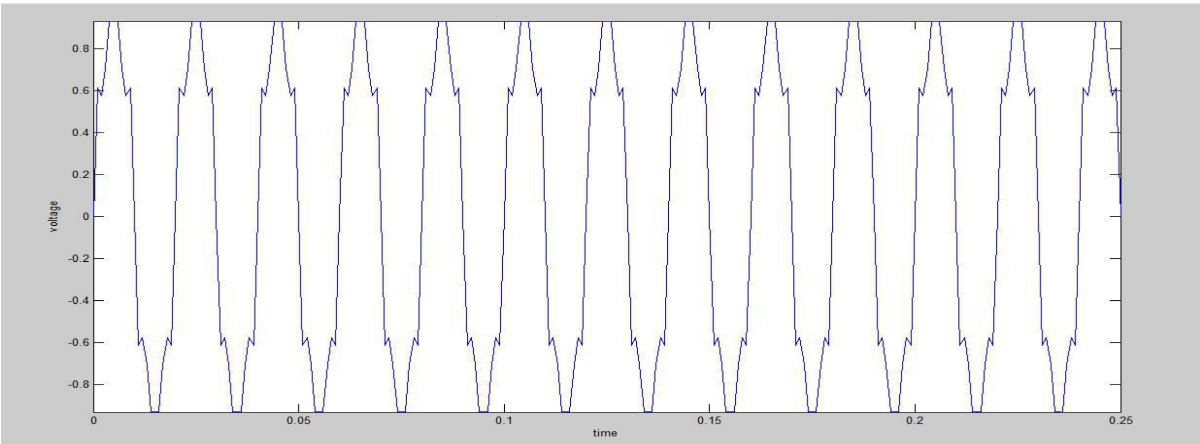

Figure 2.8 : Voltage Harmonics

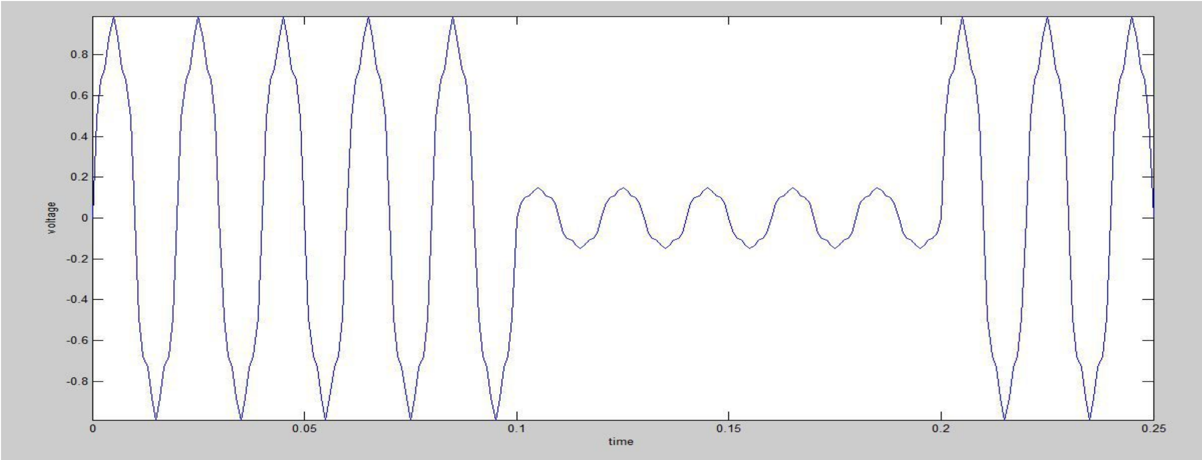

Figure 2.9 : Voltage sag with Harmonics

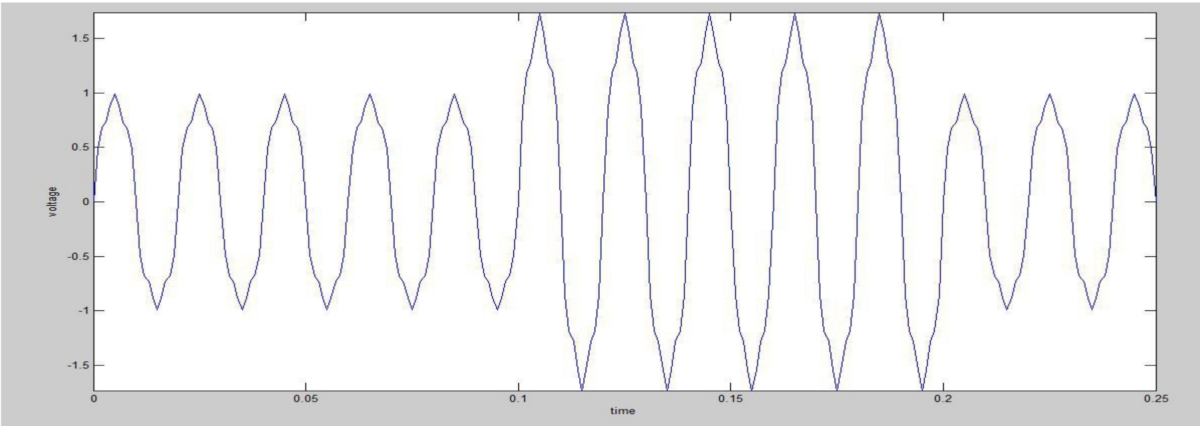

Figure 2.10 : Voltage swell with Harmonics

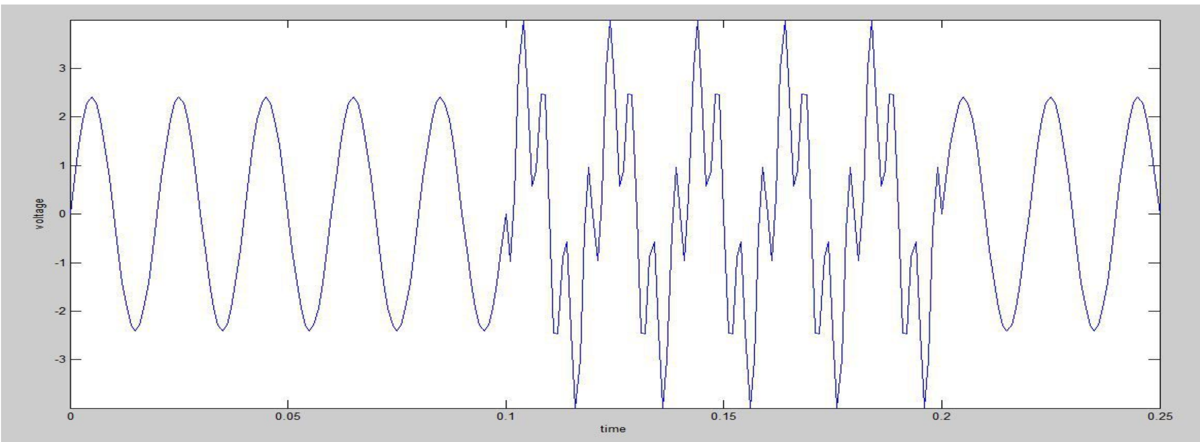

Figure 2.11 : Voltage Transient

Discussion:

The figures from 2.3 to 2.11 are various PQ disturbances generated in MATLAB using the equations with appropriate values of parameters listed in table 2.1. Here we have taken sinusoidal signal as our reference and rest are the short term disturbances in power quality.

These 9 signals are now ready for further processing i.e. Decomposition using WT algorithm which are discussed in section 2.4.

2.4 Detection using WT

Disturbances are decayed upto 4^{th} level through WT algorithm. The signal is analyzed at various resolution known as multi resolution analysis(MRA). Time resolution decreases with increase in each level and frequency scaling increases. The characterized shift of each disturbance from sinusoidal form is detected in terms of detail and approximate coefficients. One or two scale signal decay is sufficient as the decomposed signals have high time localization at lower scales.

2.4.1 Voltage Sag

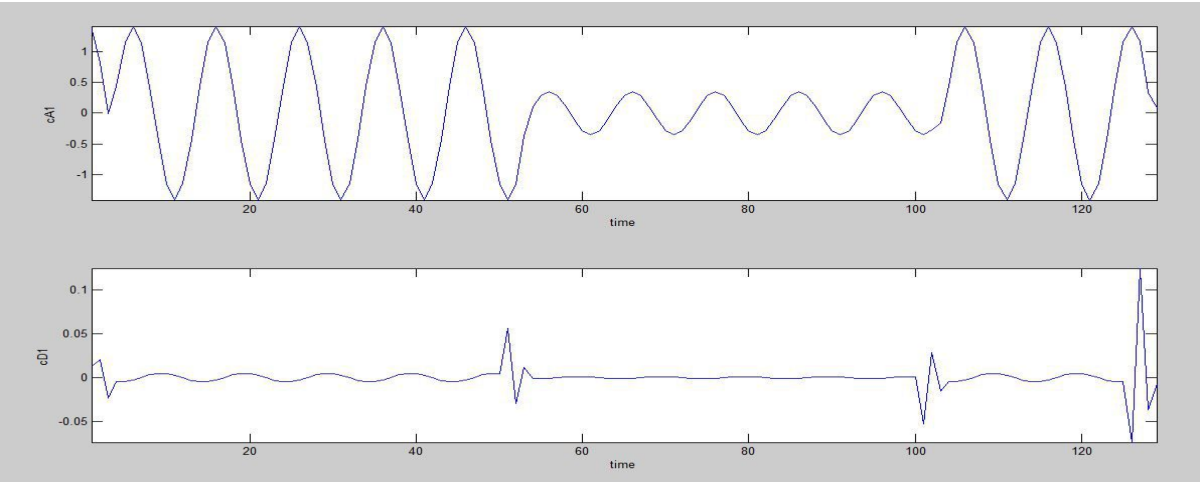

Figure 2.12 Decomposition of voltage sag level 1 using WT(approximate and detail coefficient)

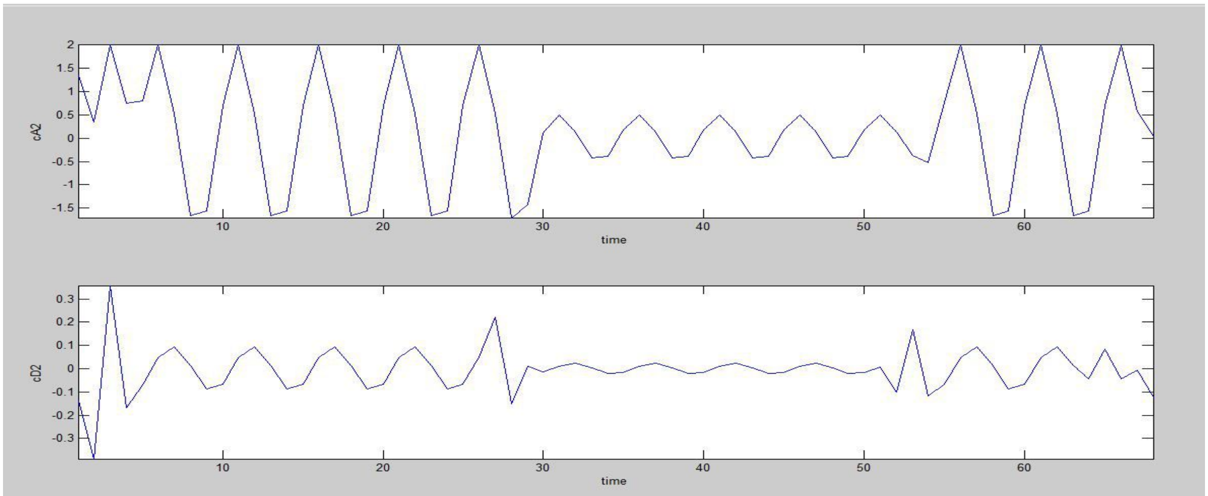

Figure 2.13 Decomposition of voltage sag level 2 using WT(approximate and detail coefficient)

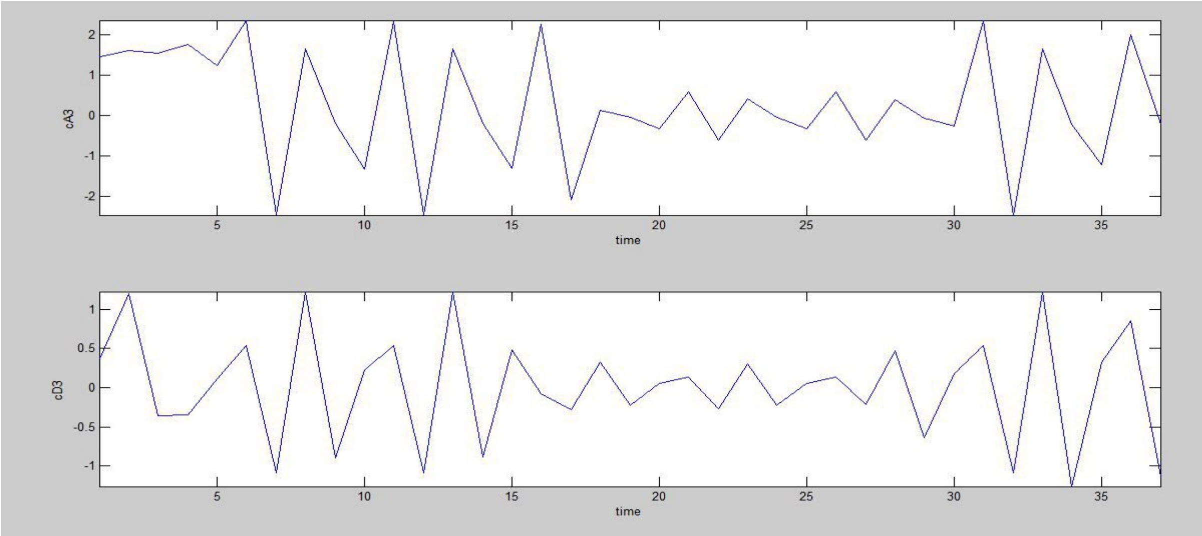

Figure 2.14 Decomposition of voltage sag level 3 using WT(approximate and detail coefficient)

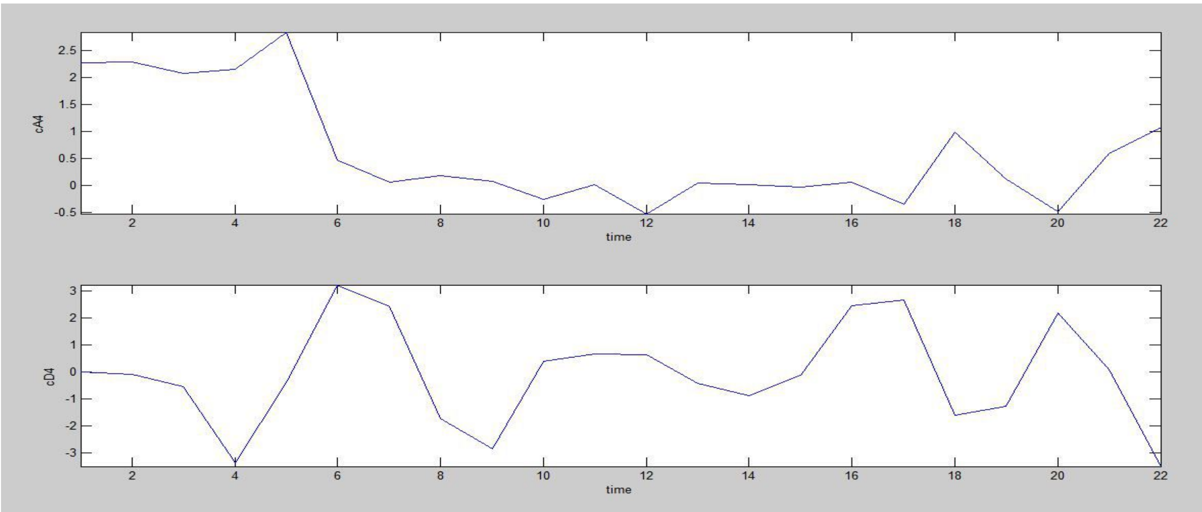

Figure 2.15 Decomposition of voltage sag level 4 using WT(approximate and detail coefficient)

Discussion:

The figures from 2.12 to 2.15 represents the decomposed version signals at level 1,2,3 and 4 respectively when **voltage sag** signal is applied to the decomposition algorithm shown in figure 2.1. Here cA1, cA2, cA3 and cA4 are the approximation coefficients in level 1.,2,3 and 4 respectively. Similarly cD1,cD2,cD3 and cD4 are the detail coefficients in various levels. All these signals represents the signal at various scale and resolution in wavelet domain. In each level the signals are down-sampled to avoid data redundancy problem as per Nyquist's rule.

2.4.2 Voltage Swell

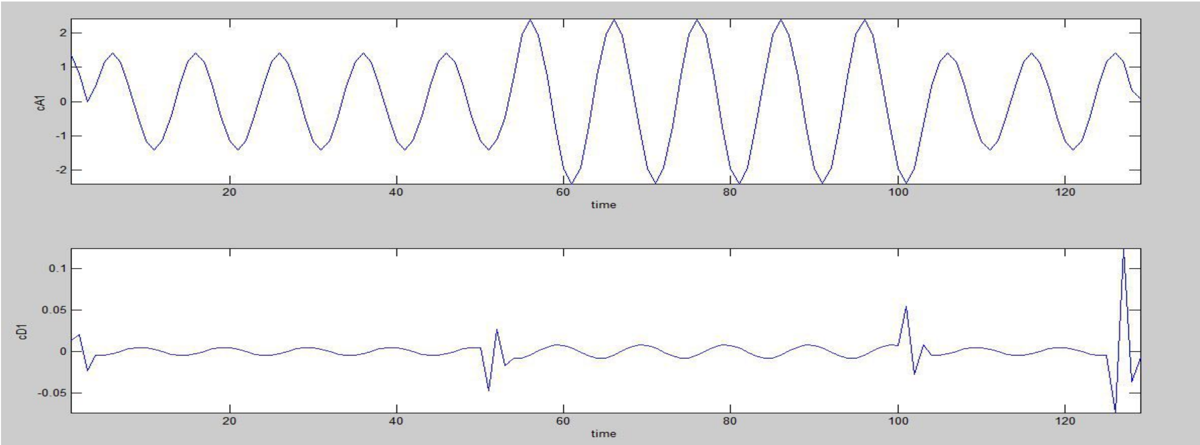

Figure 2.16 Decomposition of voltage swell level 1 using WT(approximate and detail coefficient)

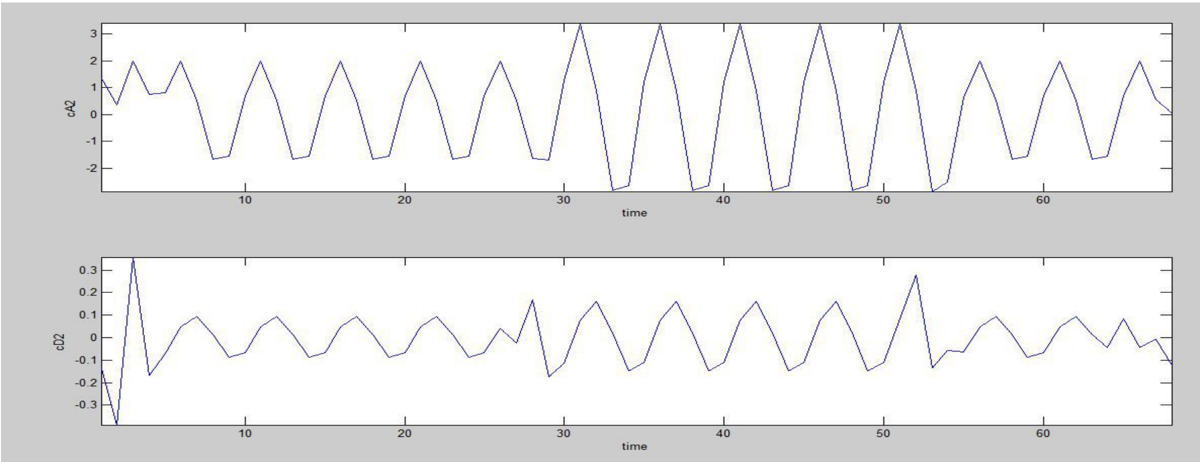

Figure 2.17 Decomposition of voltage swell level 2 using WT(approximate and detail coefficient)

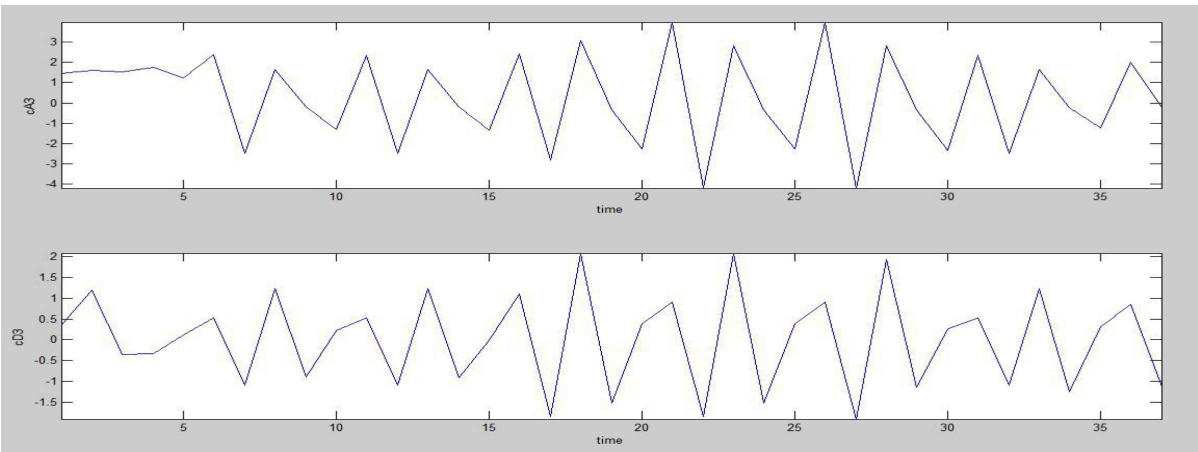

Figure 2.18 Decomposition of voltage swell level 3 using WT(approximate and detail coefficient)

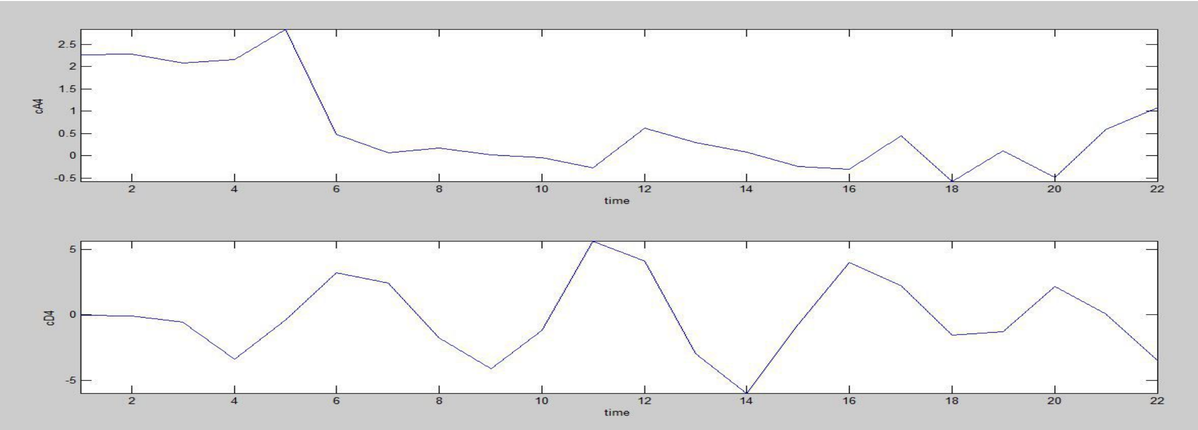

Figure 2.19 Decomposition of voltage swell level 4 using WT(approximate and detail coefficient)

Discussion:

The figures from 2.16 to 2.19 represents the decomposed version signals at level 1,2,3 and 4 respectively when **voltage swell** signal is applied to the decomposition algorithm shown in figure 2.1. Here cA1, cA2, cA3 and cA4 are the approximation coefficients in level 1.,2,3 and 4 respectively. Similarly cD1,cD2,cD3 and cD4 are the detail coefficients in various levels. All these signals represents the signal at various scale and resolution in wavelet domain. In each level the signals are down-sampled to avoid data redundancy problem as per Nyquist's rule

2.4.3 Voltage interruption

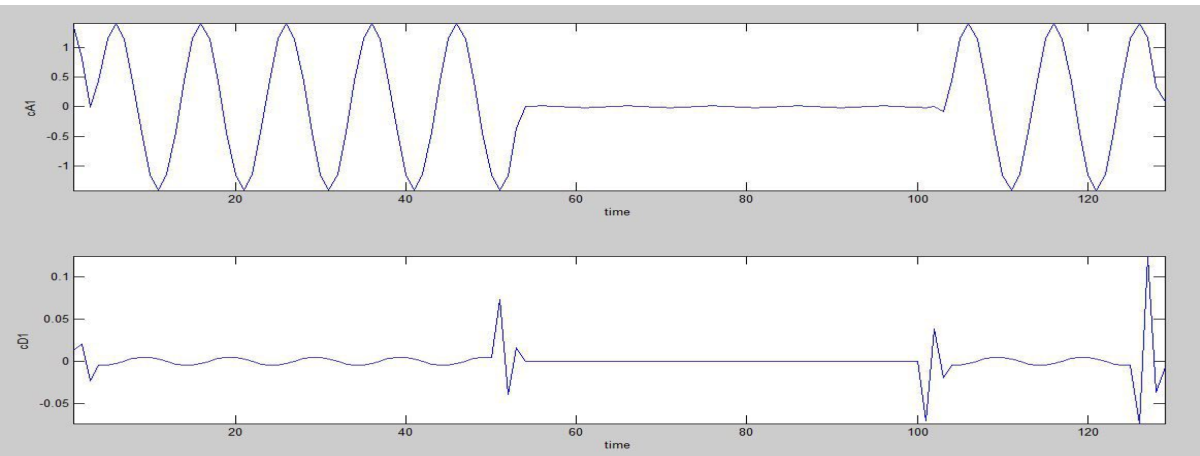

Figure 2.20 Decomposition of voltage interruption level 1 using WT(approximate and detail coefficient)

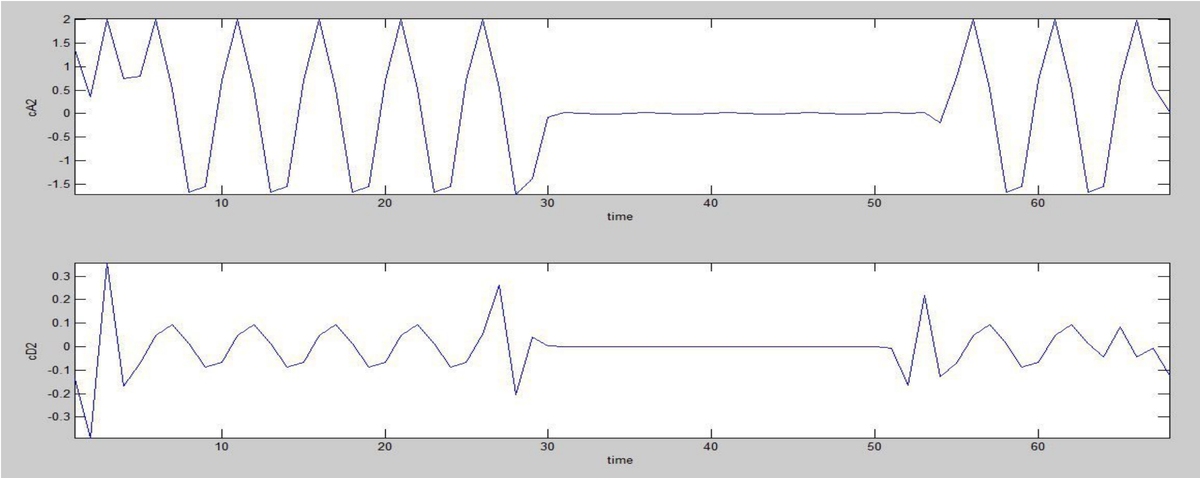

Figure 2.21 Decomposition of voltage interruption level 2 using WT(approximate and detail coefficient)

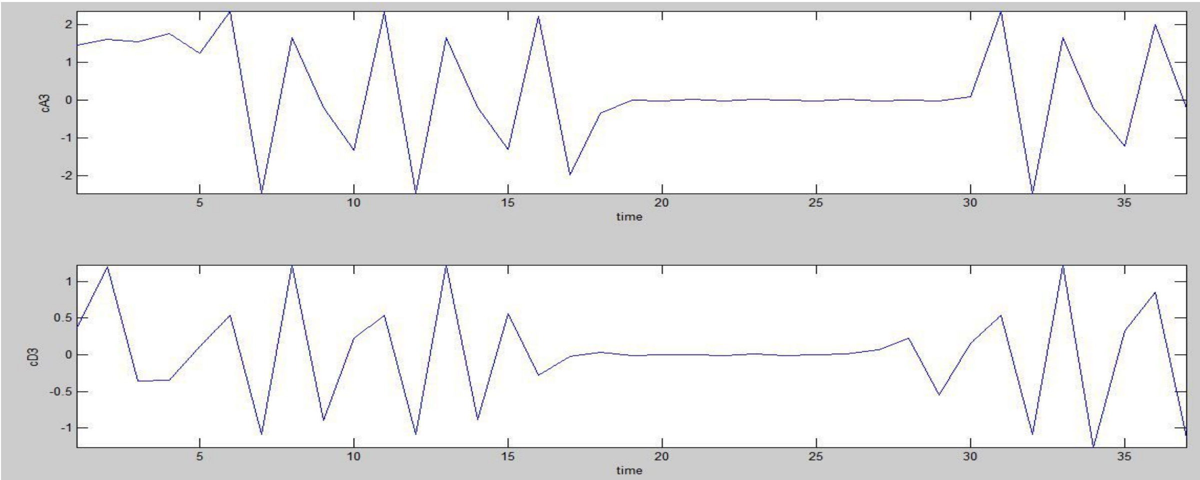

Figure 2.22 Decomposition of voltage interruption level 3 using WT(approximate and detail coefficient)

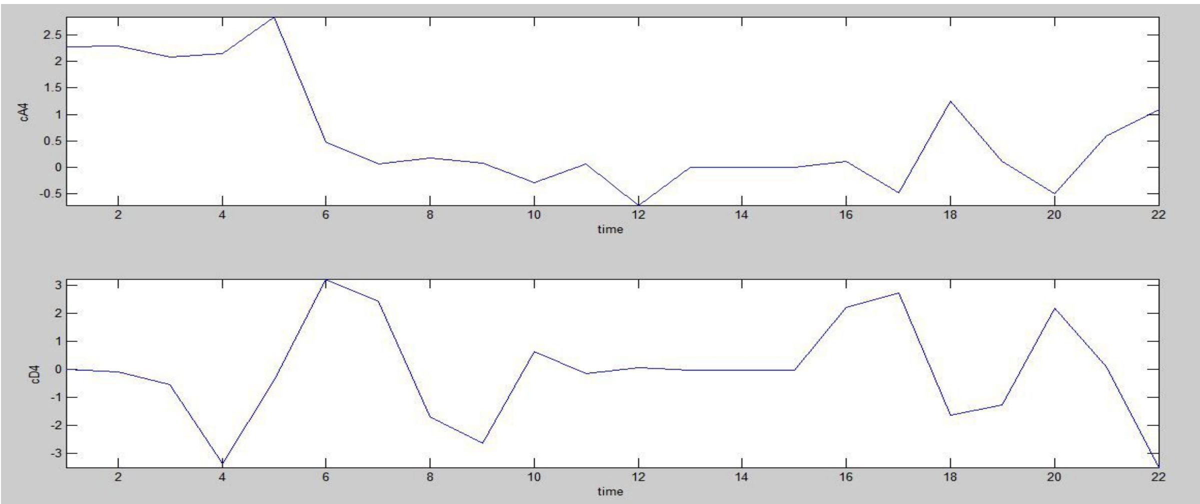

Figure 2.23 Decomposition of voltage interruption level 4 using WT(approximate and detail coefficient)

Discussion:

The figures from 2.20 to 2.23 represents the decomposed version signals at level 1,2,3 and 4 respectively when **voltage interruption** signal is applied to the decomposition algorithm shown in figure 2.1. Here cA1, cA2, cA3 and cA4 are the approximation coefficients in level 1.,2,3 and 4 respectively. Similarly cD1,cD2,cD3 and cD4 are the detail coefficients in various levels. All these signals represents the signal at various scale and resolution in wavelet domain. In each level the signals are down-sampled to avoid data redundancy problem as per Nyquist's rule.

2.4.4 Voltage Flicker

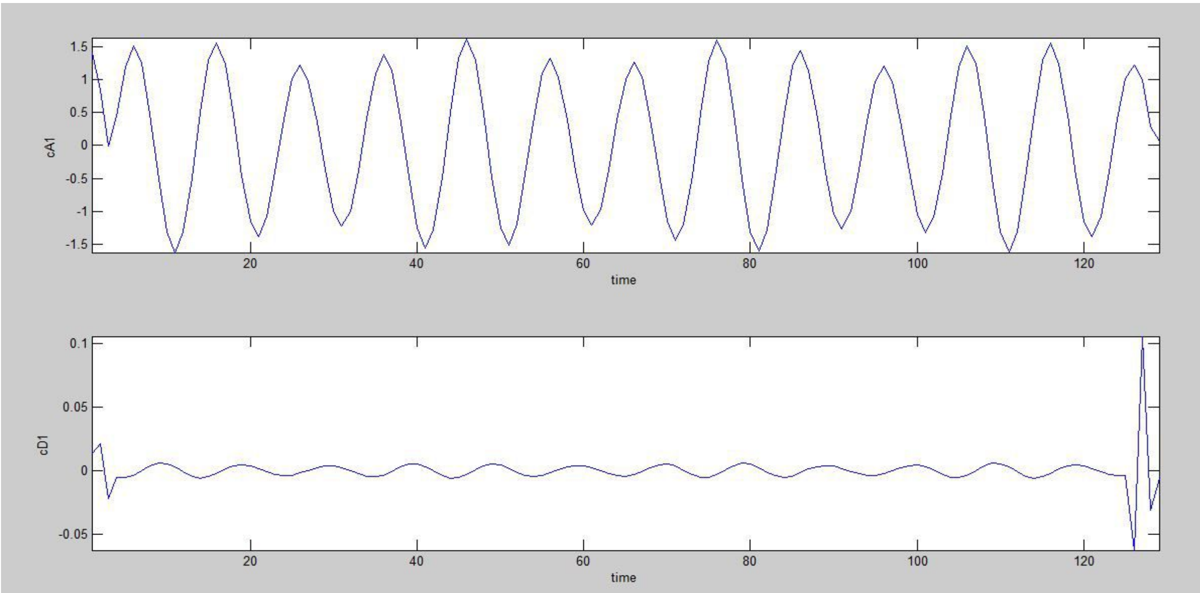

Figure 2.24 Decomposition of voltage flicker level 1 using WT(approximate and detail coefficient)

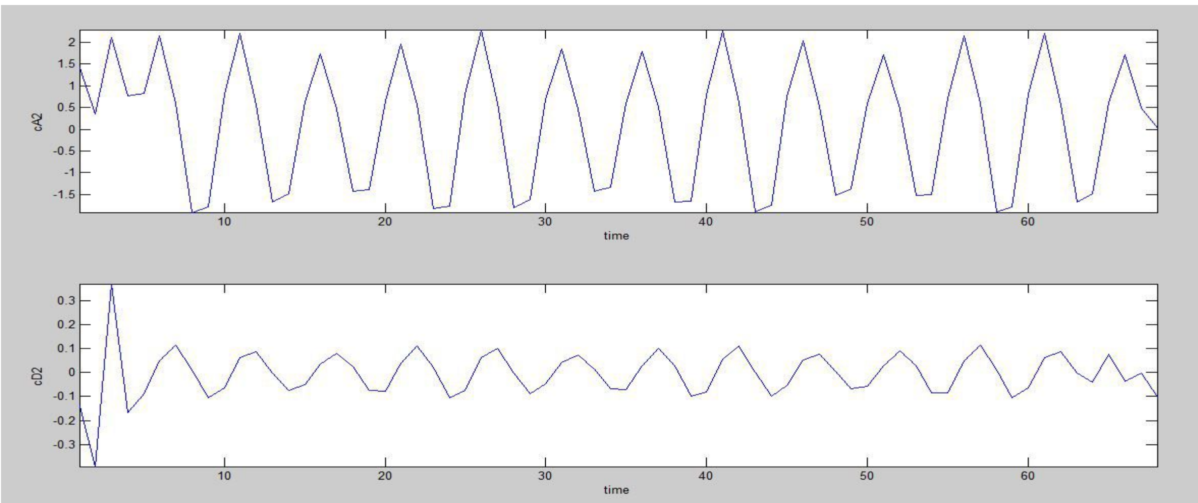

Figure 2.25 Decomposition of voltage flicker level 2 using WT(approximate and detail coefficient)

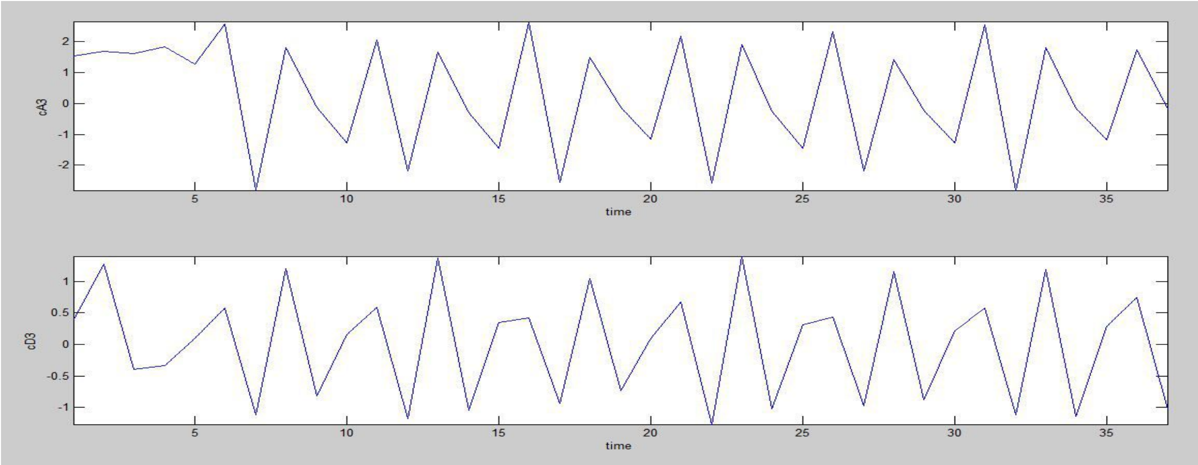

Figure 2.26 Decomposition of voltage flicker level 3 using WT(approximate and detail coefficient)

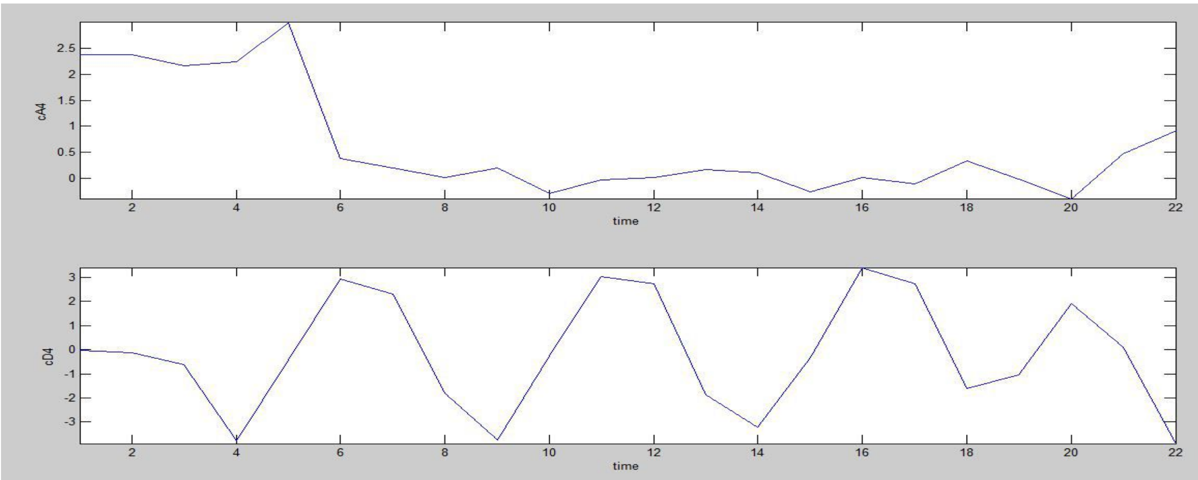

Figure 2.27 Decomposition of voltage flicker level 4 using WT(approximate and detail coefficient)

Discussion:

The figures from 2.24 to 2.27 represents the decomposed version signals at level 1,2,3 and 4 respectively when **voltage flicker** signal is applied to the decomposition algorithm shown in figure 2.1. Here cA1, cA2, cA3 and cA4 are the approximation coefficients in level 1.,2,3 and 4 respectively. Similarly cD1,cD2,cD3 and cD4 are the detail coefficients in various levels. All these signals represents the signal at various scale and resolution in wavelet domain. In each level the signals are down-sampled to avoid data redundancy problem as per Nyquist's rule.

2.4.5 Voltage Sag with harmonics

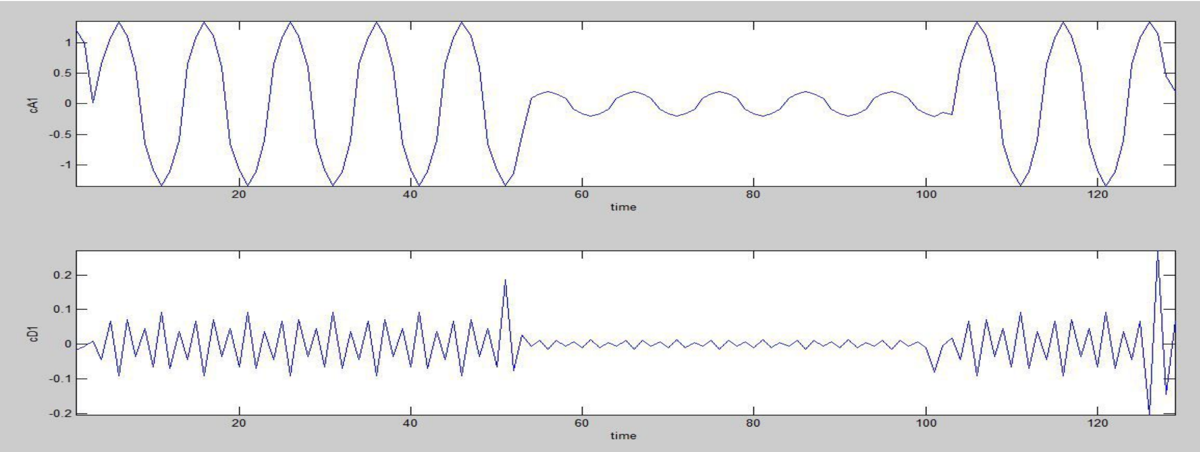

Figure 2.28 Decomposition of Sag-harmonics Voltage level 1 using WT (approximate and detail coefficient)

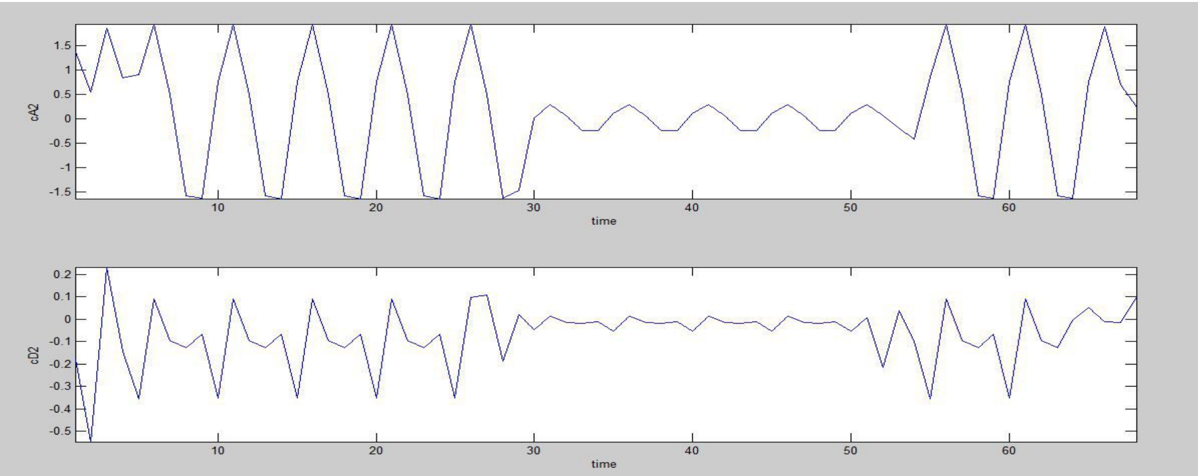

Figure 2.29 Decomposition of Sag-harmonics Voltage level 2 using WT (approximate and detail coefficient)

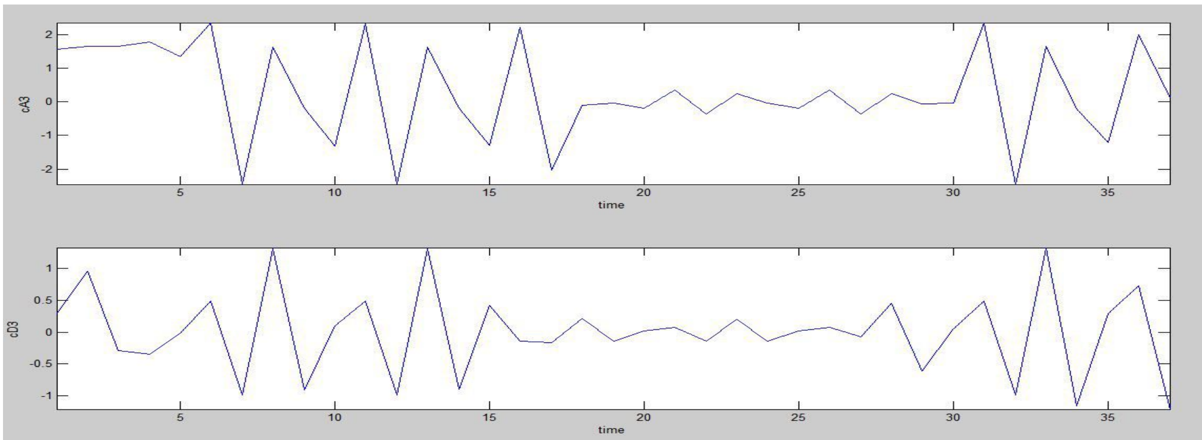

Figure 2.30 Decomposition of Sag-harmonics Voltage level 3 using WT (approximate and detail coefficient)

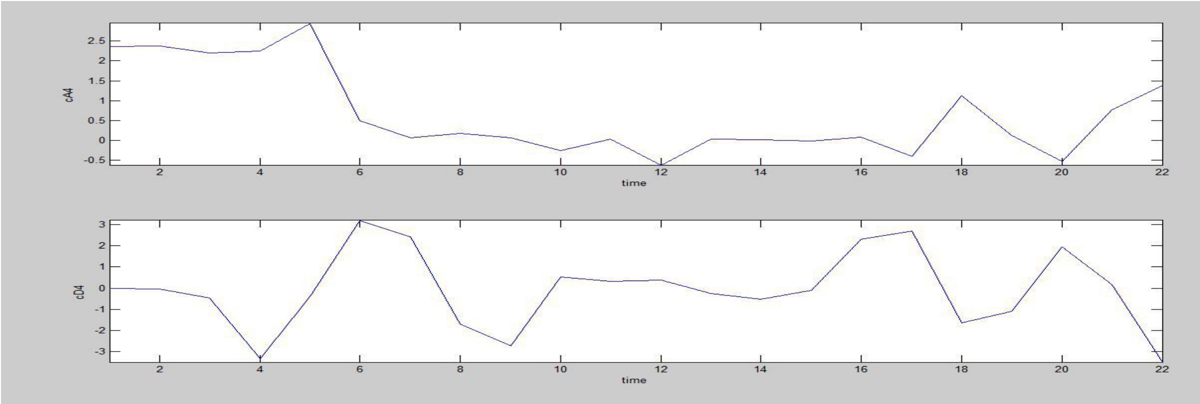

Figure 2.31 Decomposition of Sag-harmonics Voltage level 4 using WT (approximate and detail coefficient)

2.4.6 Voltage Swell with harmonics

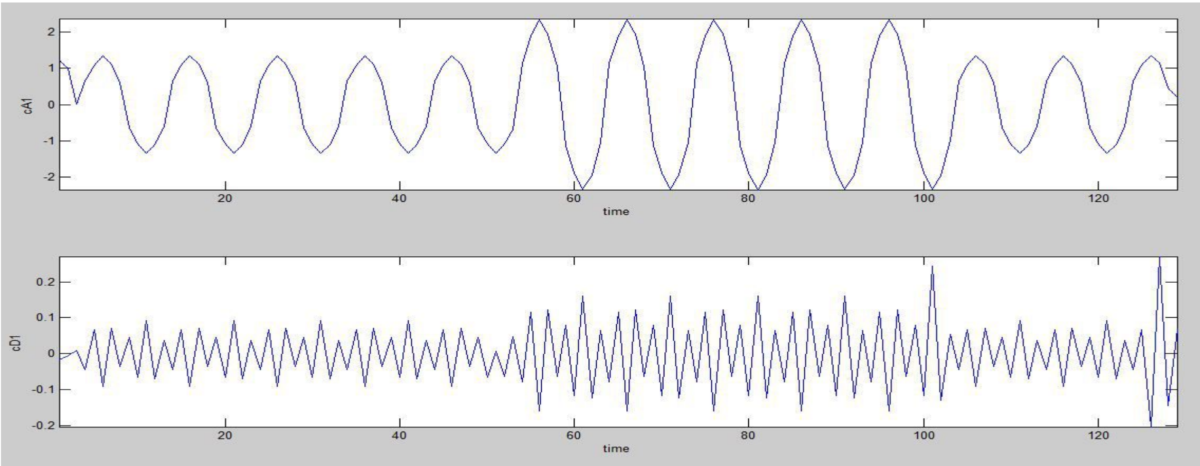

Figure 2.32 Decomposition of Swell-harmonics Voltage level 1 using WT (approximate and detail coefficient)

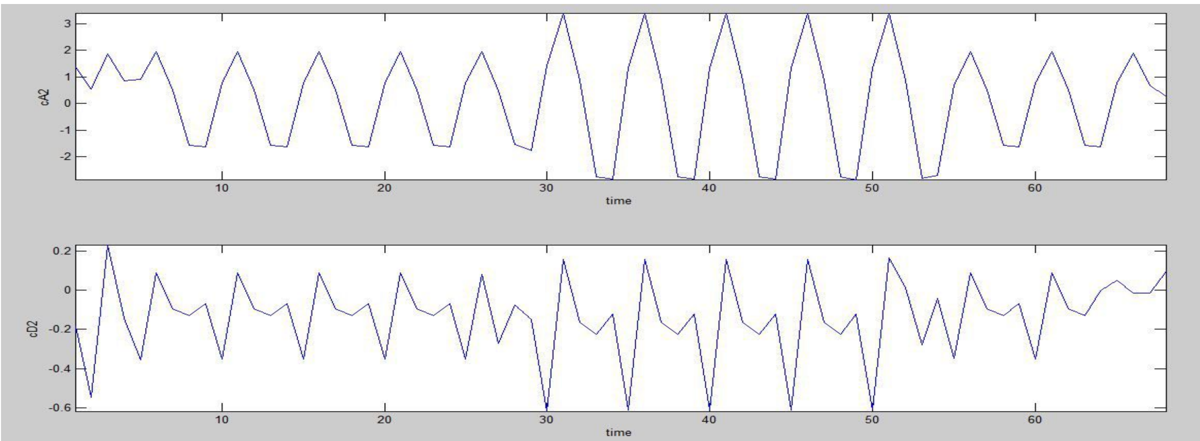

Figure 2.33 Decomposition of Swell-harmonics Voltage level 2 using WT (approximate and detail coefficient)

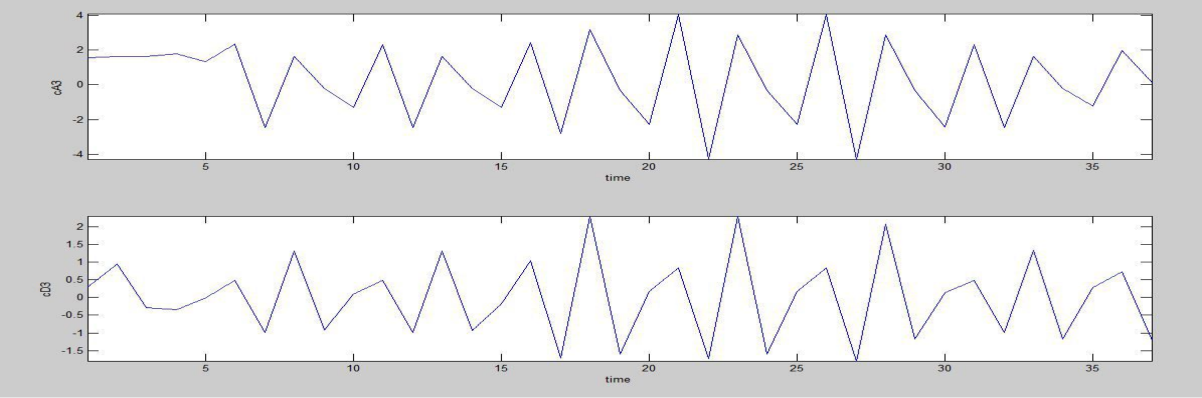

Figure 2.34 Decomposition of Swell-harmonics Voltage level 3 using WT (approximate and detail coefficient)

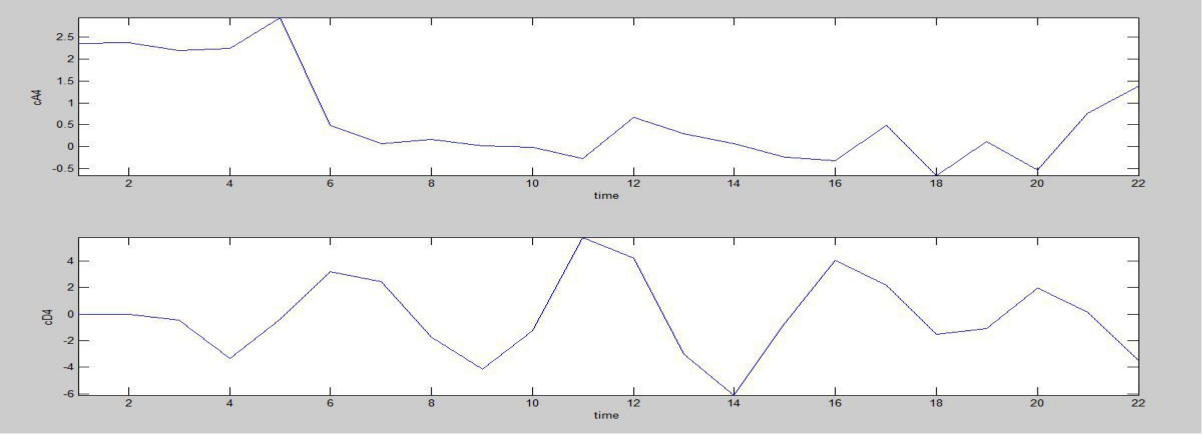

Figure 2.35 Decomposition of Swell-harmonics Voltage level 4 using WT (approximate and detail coefficient)

Discussion:

The figures from 2.32 to 2.35 represents the decomposed version signals at level 1,2,3 and 4 respectively when **swell-harmonics voltage** signal is applied to the decomposition algorithm shown in figure 2.1. Here cA1, cA2, cA3 and cA4 are the approximation coefficients in level 1.,2,3 and 4 respectively. Similarly cD1,cD2,cD3 and cD4 are the detail coefficients in various levels. All these signals represents the signal at various scale and resolution in wavelet domain. In each level the signals are down-sampled to avoid data redundancy problem as per Nyquist's rule.

2.5 Summary

Results reveals that for designing a monitoring system for PQ events, Wavelet transform can be employed effectively. Various PQ disturbances are decomposed up to four levels and disturbance points are located. These signals are now ready for extracting various features like THD,Energy which will be used in Artificial scheme for classifying the signal.

CHAPTER 3

FEATURE EXTRACTION

3.1 Preface

For indicating the type of PQ disturbance occurring in the power system feature extraction will be an important task . A database is prepared for distinguishing various PQ disturbances. In this paper, Energy and total harmonic distortion (THD) of signal are used for feature extraction and preparing the database. These are fed to the fuzzy system as input for the characterization of PQ signals.

3.2 Feature vector

3.2.1 Total harmonic distortion

Distortion harmonics is detected using the approximation and the detailed coefficients in terms of RMS value as

$$RMS = \sqrt{\frac{1}{N_j}\sum_n \left[cD_j(n)\right]^2} \qquad \text{.......................... (3.1)}$$

Where N_j depicts no of detailed coefficients at j^{th} scale and THD is found by considering the sub-bands. 6.4 kHz or $128f_1$ is sampling frequency selected and 50 Hz is the fundamental frequency with six level of WT

$$THD = \frac{\sqrt{\frac{1}{N_j}\sum_n \left[cD_j(n)\right]^2}}{\sqrt{\frac{1}{N_6}\sum_n \left[cA_6(n)\right]^2}} \qquad \text{............................ (3.2)}$$

Where N_j depicts no of detailed coefficients at scale *j.*

3.2.2 Energy content of the signal

Signal energy is determined by Parse val's theorem that states that if *S(t)* is the current through the resistor or the voltage across the resistor then the energy dissipated

$$E = \int_{-\infty}^{\infty} \left|S(t)\right|^2 dt \qquad \text{............................ (3.3)}$$

Here signal is decayed into detailed and approximate coefficients and energy dissipated in terms of these coefficients is given as

$$E = \sum_k |C_j(k)|^2 + \sum_{j=1}^{J} \sum_k |D_j(k)|^2 \quad \text{....................... (3.4)}$$

Where $D_j(k)$ is jth level detailed coefficient and $C_j(k)$ is jth level approximate coefficient

3.3 Database of different PQ disturbances

A database of THD and Energy of different PQ disturbances is prepared

3.3.1 Voltage Sag

It is a decrease of 10-90% of the rated voltage for duration of 0.5 cycles to 1 min.Hence a data base of Energy and THD is prepared for 10-90% drop in system voltage. Table 3.1 shows the feature vector for voltage sag.

Table 3.1 Feature vector for voltage sag

MAGNITUDE OF DISTURBANCE(%)	THD	ENERGY(volt^2 –sec)
10	0.7496	1.7078
20	0.7499	9.3818
30	0.7504	19.2858
40	0.7506	32.2026
50	0.7509	51.1322
60	0.7513	71.0746
70	0.7515	85.0928
80	0.7516	99.7708
90	0.7518	109.3004

3.3.2 Voltage swell

It is a rise of 10-90% in the voltage for 0.5 cycles to 1 min. Hence a data base of Energy and THD is prepared for 10-90% rise in system voltage or 110-190% of magnitude of fault. Table 3.2 shows the feature vector for voltage swell.

Table 3.2 Feature vector for voltage swell

MAGNITUDE OF DISTURBANCE(%)	THD	ENERGY(volt^2 –sec)
110	0.9616	96.7191
120	0.9621	116.7896
130	0.9627	131.7589
140	0.9631	149.6342
150	0.9638	185.2314
160	0.9649	201.5432
170	0.9661	235.8218
180	0.9675	267.0458
190	0.9691	288.5588

3.3.3 Voltage interruption

It is the loss of voltage in a power system for duration of 0.5 cycles to 1 min.Hence a database of 1-9% of magnitude of fault is prepared which is shown in Table 3.3.

Table 3.3 Feature vector for voltage interruption

MAGNITUDE OF DISTURBANCE(%)	THD	ENERGY(volt^2 –sec)
1	0.5587	92.4786
2	0.5591	93.1682
3	0.5597	95.3228
4	0.5602	97.2188
5	0.5604	100.3708
6	0.5608	103.7788
7	0.5613	105.4428
8	0.5614	106.3628
9	5616	107.7888

3.3.4 Voltage sag with harmonics

Table 3.4 shows the feature vector for voltage sag with harmonics of 3rd order harmonics.

Table 3.4 Feature vector for voltage sag with 3rd order harmonics

MAGNITUDE OF DISTURBANCE(%)	THD	ENERGY(volt^2 –sec)

10	0.5297	0.9151
20	0.5301	21.0633
30	0.5317	44.9673
40	0.5349	82.8841
50	0.5365	112.8173
60	0.5387	157.7561
70	0.5403	199.7113
80	0.5414	243.6793
90	0.5424	288.5588

3.3.5 Voltage swell with harmonics

Table 3.5 shows the feature vector for voltage swell with 3rd order harmonics.

Table 3.5 Voltage swell with 3rd order harmonics

MAGNITUDE OF DISTURBANCE(%)	THD	ENERGY(volt^2 –sec)
110	0.9342	292.8127
120	0.9345	354.5753
130	0.9351	463.7353
140	0.9357	503.9081
150	0.9361	594.0937
160	0.9364	684.2921
170	0.9367	768.5033
180	0.9369	812.7273
190	0.9372	873.5981

3.4 Summary

In this chapter feature vectors containing Energy and THD are extracted. This chapter reveals that THD and Energy is increased considerably in case of harmonics. These vectors will be used in designing a fuzzy expert system for the classification purpose.

CHAPTER 4

IMPLEMENTATION OF
FUZZY EXPERT SYSTEM
TO CHARACTERIZE
PQ DISTURBANCES

4.1 Preface

Fuzzy logic (FL) refers to a logic system which depicts knowledge and reasons in a fuzzy manner for reasoning under uncertainty [7].It models the imprecise modes of reasoning which has an important role in human ability to obtain an approximate answer for a question that is not exact, not complete or not totally reliable. It is hence suitable to use fuzzy logic when a mathematical model is too difficult to model and too complex to be evaluated. The accuracy of such systems is based on the knowledge of human hence, its feasibility depends on the validity of rules. Here a fuzzy expert system basing upon certain rules is implemented to characterize various PQDs.

4.2 Fuzzy logic system

A Fuzzy Logic system is an algorithm to monitor a fuzzy relation between data of process conditions to be monitored and the monitor action. It gives a fuzzy model developed based on human expertise. A set of simple linguistic rule determines the control action. The internal structure of a FL system is shown in Figure 4.1.

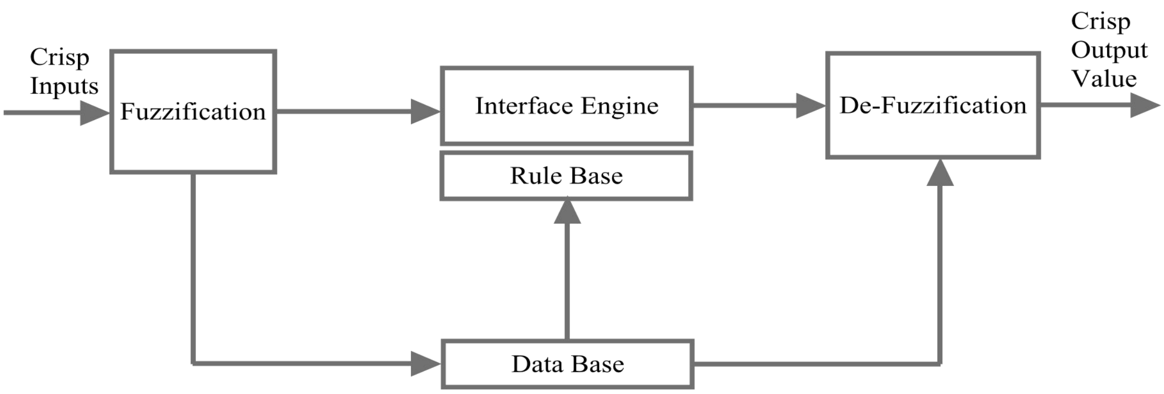

Figure 4.1 Internal structure of Fuzzy logic system

The main components of the system are:

1. Fuzzification: This unit converts a crisp input into a linguistic variable .
2. Rule Base: This controls the classification using If-then rules.
3. Defuzzification: This converts fuzzy value to a crisp output.

4.3 Implementation of fuzzy expert system

Fuzzy expert system uses the extracted features THD and Energy of various PQ disturbances as input to characterize them as we have seen in Figure 1.3. The output of the system will characterize the type of disturbance as well as it will depict whether the disturbance will contain harmonics or not.

Two features like THD and ENERGY which is inherent to all disturbances is obtained and a database is prepared. Based on this a fuzzy expert system is modeled.

TABLE 4.1 DATA BASE OF FEATURES EXTRACTED

Type of fault	Range of fault	Range of Energy	Range of THD
Interruption	1% to 9% of fault	92.4786 to 107.7088(R)	0.5587 to 0.5616(C)
Sag	10% to 90% of fault	1.7078 to 109.3004 (P)	0.7496to 0.7518(A).
Swell	110% to 190% of fault	96.7191 to 288.5588 (Q)	0.9666 to 0.9691(B)
Sag with harmonics	3rd	0.9151 to74.1263 (S)	0.5397 to 0.5424(D)
Swell with harmonics	3rd	292.8127 to 873.5981 (T)	0.9342 to 0.9372(E)

4.3.1 Membership functions

Out of various Membership functions available triangular membership function is the simplest and most commonly used which is described through three points forming a triangle. For convenience here triangular membership function is used. The fuzzy expert system implemented here uses two input variables Energy and THD whereas the two output variables are “Type of disturbance” and “Pure or harmonics”. Energy has five membership functions corresponding to the energy level of different disturbances while THD has five membership functions. Output1 i.e type of disturbance has three membership functions and output2 i.e. pure or harmonic disturbance has two input variables.

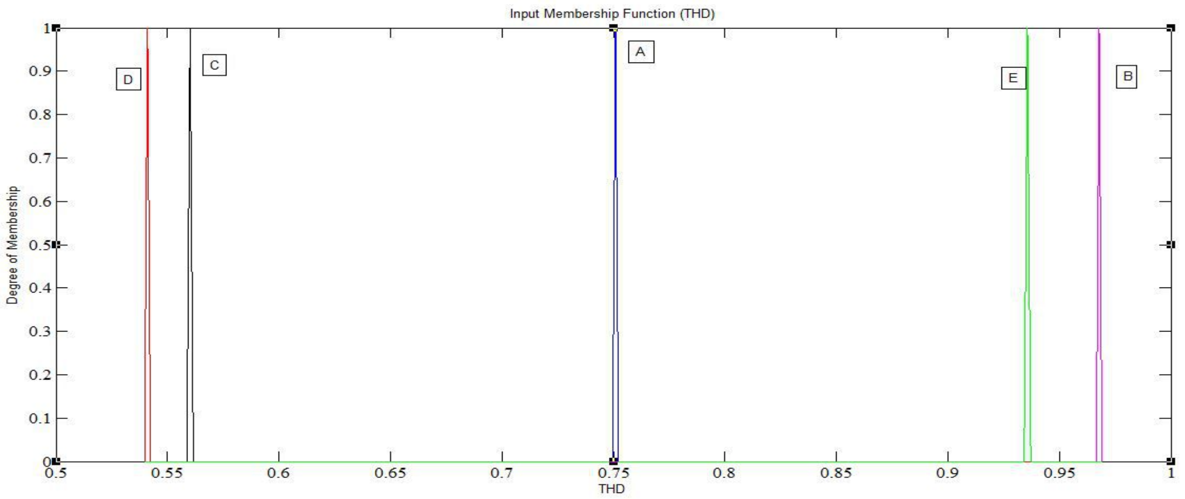

FIG 4.2 :- INPUT MEMBERSHIP FUNCTION (THD)

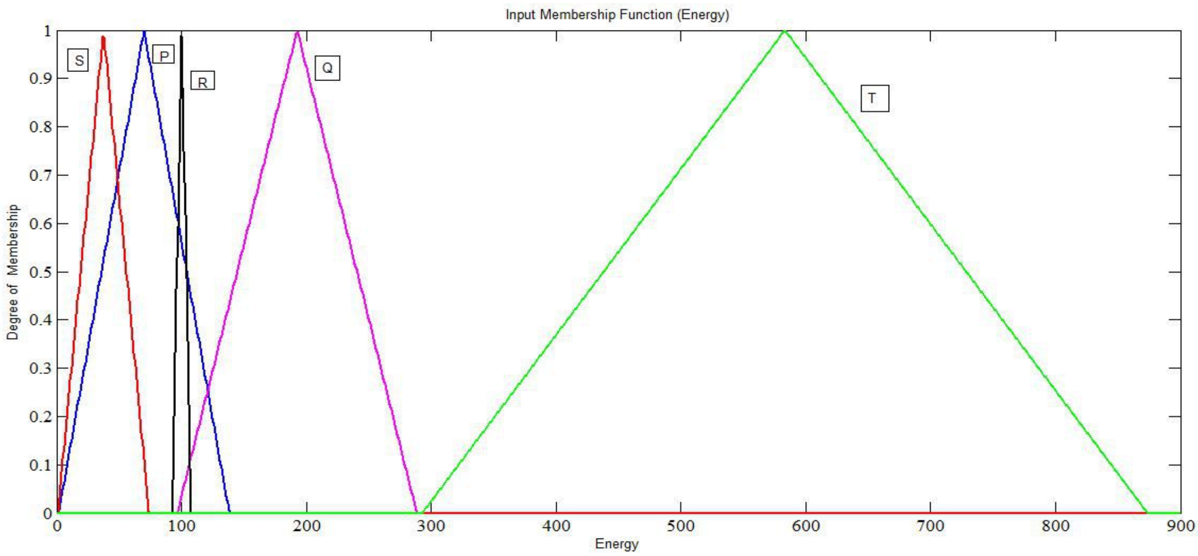

FIG 4.3 :- INPUT MEMBERSHIP FUNCTION (ENERGY)

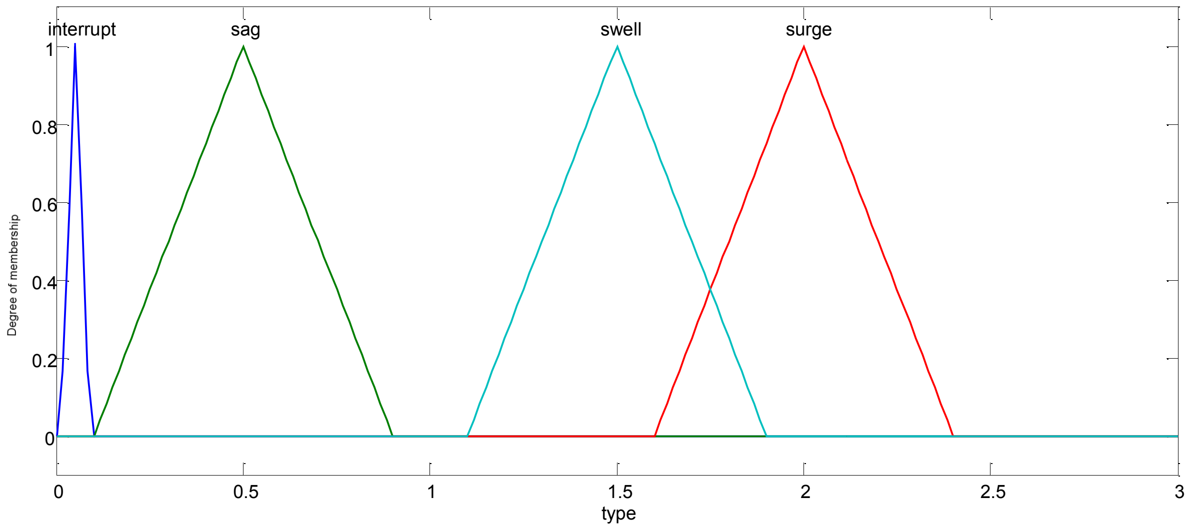

FIG 4.4 :- OUTPUT MEMBERSHIP FUNCTION 1

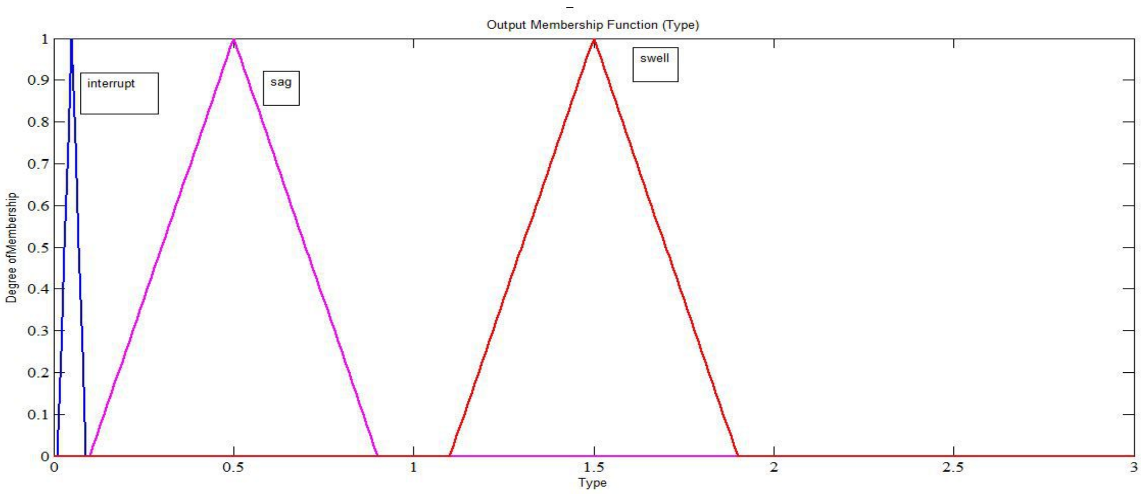

FIG 4.5 :- OUTPUT MEMBERSHIP FUNCTION 2

FIG 4.2 and FIG 4.3 represents the input membership function for THD and Energy respectively. Energy has five membership functions in terms of linguistic variables represented as A,B,C,D and E. The THD has five membership functions named as P,Q,R,S and T. Similarly output1 (type of disturbance) has four membership functions sag,swell, surge and interruption while output2 (pure or harmonics) has two membership functions pure and harmonics.

Table 4.2 Relationship between linguistic and actual values for input membership functions

Type of disturbance	Energy	Membership function	THD	Membership function
Interruption(1% to 9% of fault)	92.4786 to 107.7088	R	0.5587 to 0.5616	C
Sag(10% to 90% of fault)	1.7078 to 109.3004	P	0.7496 to 0.7518	A
Swell(110% to 190% of fault)	96.7191 to 288.5588	Q	0.9616 to 0.9691	B
Sag with harmonics	0.9151 to 288.5588	S	0.5397 to 0.5424	D
Swell with harmonics	292.8127 to 873.5981	T	0.9342 to 0.9372	E

Table 4.3 Relationship between the linguistic and actual values of output membership function 1 for Type of disturbance.

Membership functions for output variable 1	Percentage of disturbance
Interruption	0.0- 0.09
Sag	0.1- 0.9
Swell	1.1- 1.9

Table 4.4 Relationship between the linguistic and actual values for output membership function 2

Membership function for output variable 2	Values
Pure	0.0- 0.5
Harmonics	0.5- 1.0

4.3.2 Rule base

There are total 25 (i.e 5*5) number of rules. Out of these only 5 rules are feasible. From the database following 5 rules are formed for the characterization purpose.

Rule 1: If Energy is R and THD is C then disturbance is Interruption.
Rule 2: If Energy is P and THD is A then disturbance is Sag.
Rule 3: If Energy is Q and THD is B then disturbance is Swell.
Rule 4: If Energy is S and THD is D then disturbance is Sag with harmonics.
Rule 5: If Energy is T and THD is E then disturbance is Swell with harmonics.

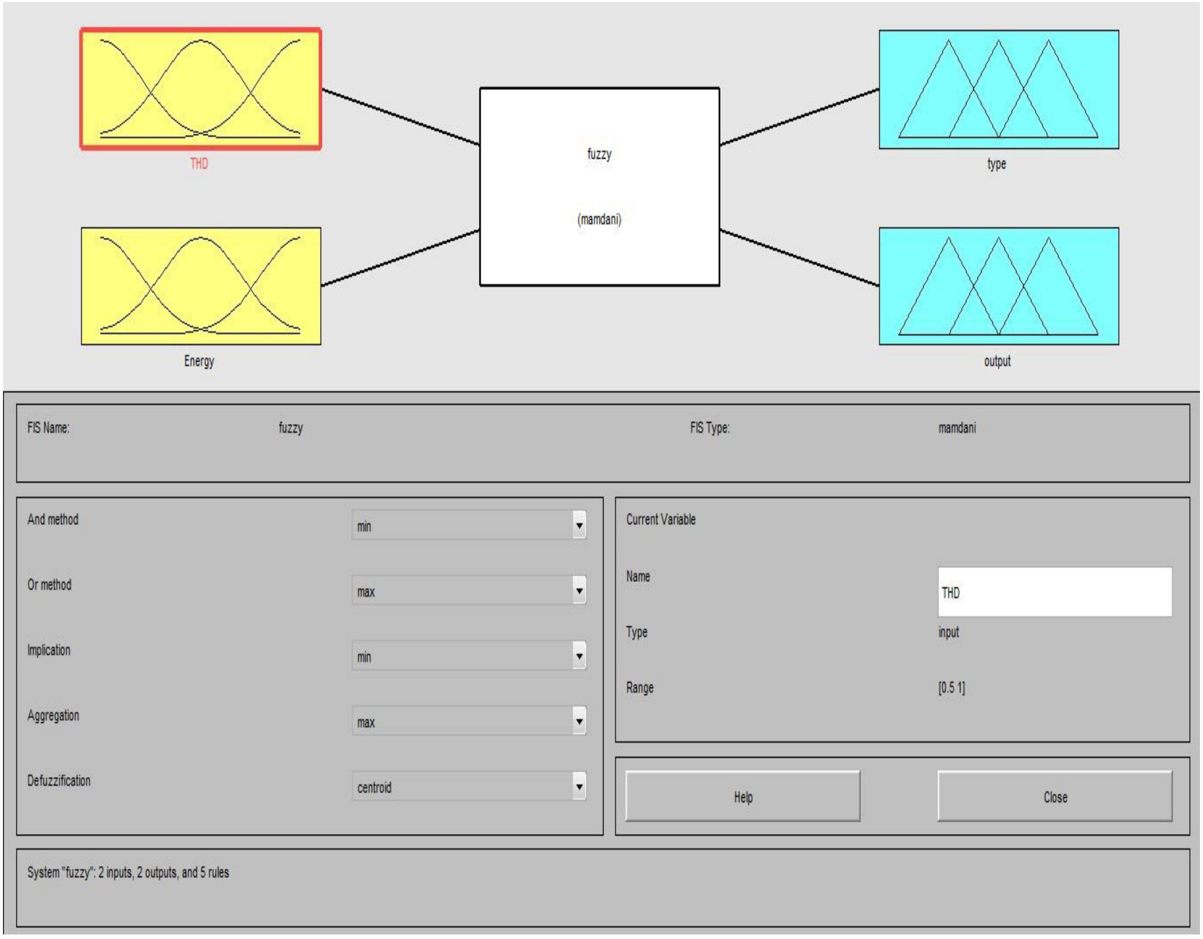

FIG 4.6 :-FIS EDITOR WINDOW FOR PQ DISTURBANCES CLASSIFICATION

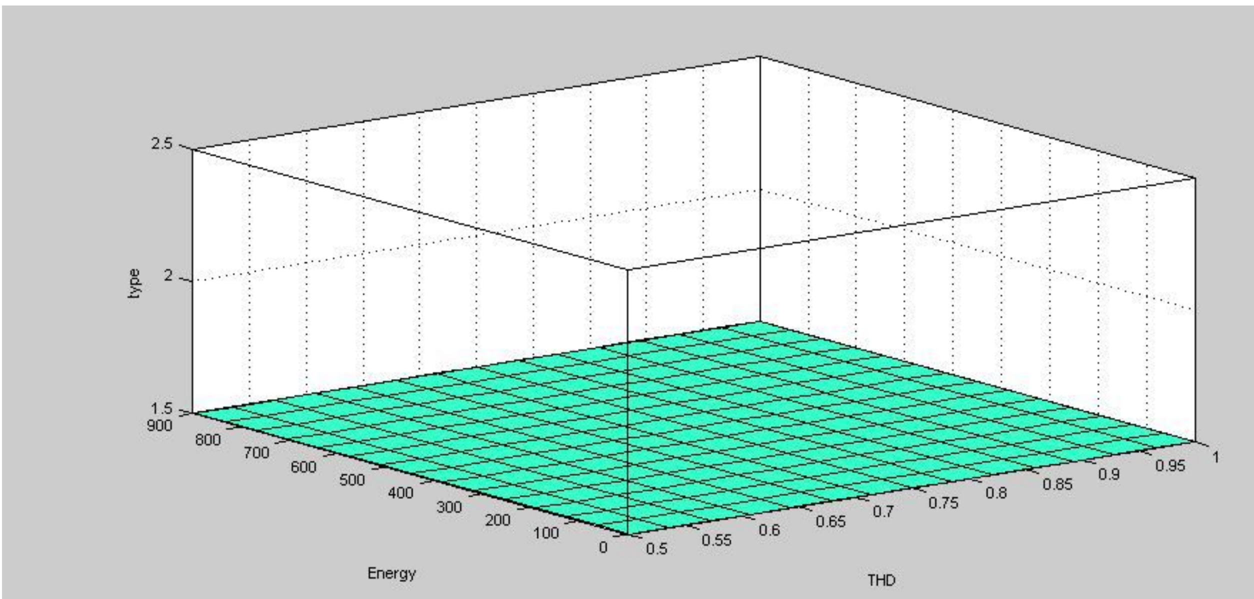

FIG 4.7 :-SURFACE PLOT OF FIS

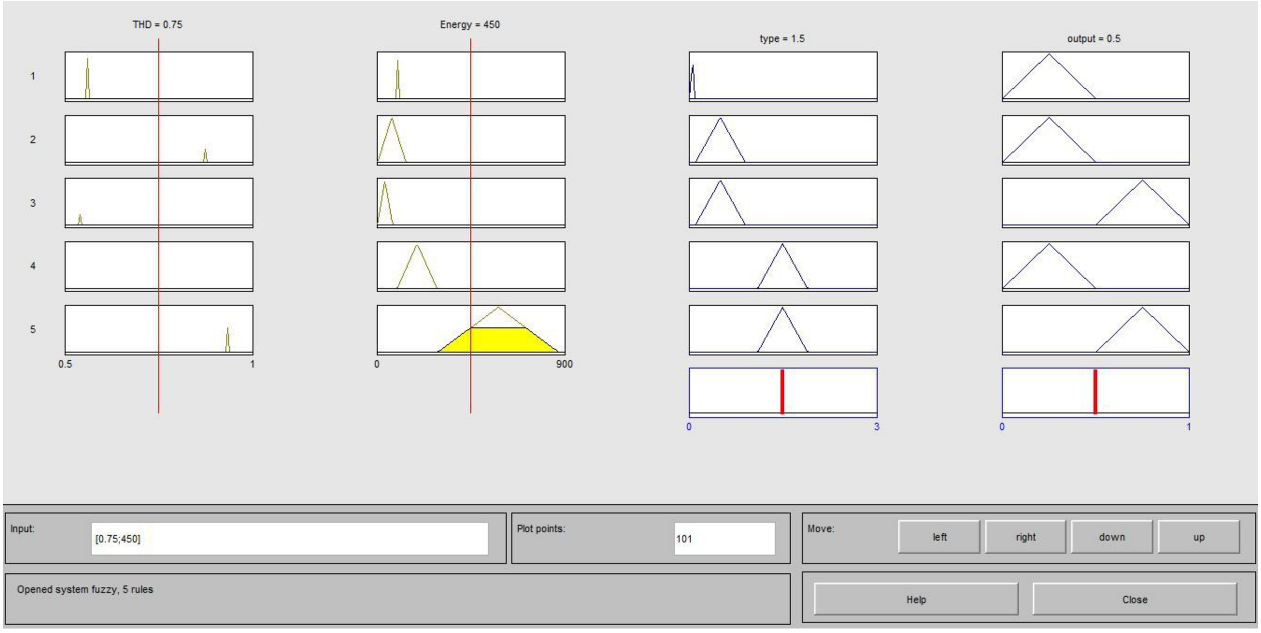

FIG 4.8 :-RULE VIEWER WINDOW FOR PQ DISTURBANCES CLASSIFICATION.

4.4 Classification Accuracy

Around hundred samples of disturbances in each class of power quality are simulated and tested with the above fuzzy expert system. The overall accuracy obtained is 93%.It shows very little in-accuracy in boundary values of different disturbance band otherwise it gives very accurate results in classifying different disturbances. This system also indicates whether the disturbance contains harmonics or not.Table.6.4 shows the statistical data for the number of samples tested. Equation (6.1) is used for calculating classification accuracy.

$$\text{Classification } Accuracy = \frac{X}{Y} \times 100 \qquad \text{............... (4.1)}$$

Where X= Number of correctly identified samples

Y= Number of samples under consideration

Table 4.5 Classification Accuracy

Type of disturbance	No of samples considered(Y)	No of Samples correctly detected(X)
Interruption	101	96
Sag	101	94

Swell	101	89
Sag with harmonics	101	96
Swell with harmonics	101	93

4.5 Summary

This chapter presents a hybrid technique based on DWT and the Fuzzy Expert system for accurate characterization of the PQ disturbances. The main advantage of this proposed technique is to classify the complicated PQ disturbances such as Sag with Harmonics and Swell with Harmonics. The features extracted in Chapter 3 are used as inputs for fuzzy expert system based on certain rules. The classification accuracy in case of swell disturbance is the lowest (i.e. 88%) whereas the overall accuracy obtained is 93% which shows the effectiveness of the system in characterizing various PQ disturbances.

CHAPTER 5

CONCLUSION
&
FUTURE SCOPE OF WORK

5.1 Conclusion

The identification and characterization of PQDs is an emerging problem in PQ issue as before any mitigation, disturbance type and disturbance point are required to apply mitigate action. Here various PQ disturbances are analyzed for characterization purpose. First the disturbances are decomposed upto 4th level using WT and the disturbance point and disturbance type are detected. Then the feature vectors are extracted. The two distinct features such as THD and Energy are used for extracting the features and a data base is prepared. Then a Mamdani rule based fuzzy expert system is designed for characterization of various PQ disturbances. Around hundred number of PQ events with varying magnitude of fault intensity are tested with the fuzzy expert system to calculate the classification accuracy which we found to be 93%. However, the Fuzzy interface system faces difficulty in classifying the extreme values in each disturbance range correctly.

5.2 Future prospects

1. Here two features are considered to design the PQD detection system using fuzzy expert system. Additional features e.g Entropy, standard deviation etc. can be considered for design and characterization.

2. In addition to triangular membership function other membership function can be used and the corresponding analysis can be carried out.

3. One more aspect is that PQ signals are required to be de-noised first for detection and feature extraction as wavelet transform is quite sensitive to the noise. Hence research must be carried out to invent other signal processing tool.

4. In addition to fuzzy expert system, we can use Neural network for PQ analysis and their characterization.

REFERENCES

1. Quinquis, “Digital Signal Processing using Matlab,” ISTE WILEY, pp.179-205, 2008.

2. P.S.Wright,”Short time fourier transform and wigner-ville distributions applied to the calibration of power frequency harmonic analyzers,” *IEEE Trans.instrum.meas.* (1999) 275-278.

3. R. Polikar, The Engineer’s Ultimate Guide to Wavelet analysis, The Wavelet Tutorial.March 1999.

4. S.Santoso, W.M.Grady,E.J.Powers,J.Lamoree and S.C.Bhatt,”Characterization of distribution power quality events with fourier and wavelet transforms,” *IEEE Trans.power delivery,*Vol.15,pp 147-150,jan.2000.

5. Abdelazeem A.Abdelsalam, Azza A.Eldesouky,Abdelhay A.Sallam,”characterization of power quality disturbances using hybrid technique of linear kalman filter and fuzzy expert system,” ELSEVIER Electric power system Reaserch 83 (2012) 31-35.

6. S. Santoso, E. Powers, W. Grady, and P. Hoffmann,” Power Quality Assessment via Wavelet Transform Analysis,” *IEEE Transactions on Power Delivery*, Vol.11, No.2, pp. 624-630, April 1996.

7. Peisheng Gao and Weilin Wu, “Power Quality Disturbances Classification Using Wavelet & Support Vector Machine,” *IEEE Proceedings of the Sixth International Conference on IntelligentSystems Design and Applications* (ISDA'06).

8. S. Tuntisak and S. Premrudeepreechacharn, “Harmonic Detection in Distribution System Using Wavelet Transform & Support Vector Machine,” *IEEE Conference on Power Tech* 2007.

9. J.S. Huang, M. Negnevitsky and D.T. Nguyen, “Wavelet transform based harmonic analysis,” Australasian universities power engineering Conference and IE Aust Electric Energy Conference, pp.112-116, 1999.

10. Boris Bizjak and Peter Planinsic, “Classification of Power Disturbances using Fuzzy Logic,”.

11. Sudipta Nath, Priyanjali Mishra,”Wavelet based Feature Extraction for Classification of Power Quality Disturbances,” ICREPQ’11 International Conference on Renewable Energies and Power Quality,13-15 April,2011.